NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

EVALUATION OF OPERATOR PERFORMANCE USING TRUE COLOR AND ARTIFICIAL COLOR IN NATURAL SCENE PERCEPTION

by

John T. Vargo

March 1999

Thesis Advisors: William K. Krebs
Second Reader: Samuel E. Buttrey

Approved for public release; distribution is unlimited.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	March 1999	Master's Thesis

4. TITLE AND SUBTITLE
EVALUATION OF OPERATOR PERFORMANCE USING TRUE COLOR AND ARTIFICIAL COLOR IN NATURAL SCENE PERCEPTION

5. FUNDING NUMBERS
N0001497WR30091
N0001498WR30112

6. AUTHOR(S)
Vargo, John T.

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Postgraduate School
Monterey, CA 93943-5000

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Lockheed Martin Corporation University Research Grant program

Office of Naval Research, Life Sciences Division, Arlington , VA

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES
The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

12a. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT *(maximum 200 words)*

Currently, the two most commonly used night optical devices employed in military operations are the long-wave infra-red sensor and the image intensified sensor. Recent advances in technology have permitted the fusion of the output of these two devices into a single color display that potentially combines the capabilities of both sensors while overcoming their limitations. Although the concept is appealing, previous sensor fusion studies have been inconclusive on the benefits of an artificially colored target. Perhaps, an artificially colored target disrupts an operator's visual processing thereby hindering the detection of a target. The purpose of this thesis is to compare the effects of artificial color, natural color, and monochrome formats in visual scene perception. It is hypothesized that participant response times and error rates would be greater at detecting an artificially colored target compared to a natural colored or a target presented achromatically. Two experiments were conducted. Experiment 1 used non-degraded imagery and Experiment 2 used degraded imagery to compare these effects. It was found that reaction time and error rates for naturally colored and achromatic images were similar and substantially less when compared to artificially colored images. For degraded scenes, natural color was more beneficial when compared to achromatic and artificially colored scenes. Additionally, artificially colored scenes caused extremely large error rates and reaction times. These results will provide algorithm developers insight into the importance of color constancy.

14. SUBJECT TERMS
Sensor Fusion, Human Factors, Night Vision Devices, Target Recognition, Human Visual System, Natural Scene Perception, Artificial Color, Natural Color

15. NUMBER OF PAGES
137

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFI- CATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited

EVALUATION OF OPERATOR PERFORMANCE USING TRUE COLOR AND ARTIFICIAL COLOR IN NATURAL SCENE PERCEPTION

John T. Vargo
Lieutenant Commander, United States Navy
B.S., United States Naval Academy, 1982

Submitted in partial fulfillment of the
Requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
March 1999

Author: John T. Vargo

John T. Vargo

Approved by: William K. Krebs

William K. Krebs, Thesis Advisor

Samuel E. Buttrey

Samuel E. Buttrey, Second Reader

Richard E. Rosenthal

Richard E, Rosenthal, Chairman
Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Currently, the two most commonly used night optical devices employed in military operations are the long-wave infra-red sensor and the image intensified sensor. Recent advances in technology have permitted the fusion of the output of these two devices into a single color display that potentially combines the capabilities of both sensors while overcoming their limitations. Although the concept is appealing, previous sensor fusion studies have been inconclusive on the benefits of an artificially colored target. Perhaps, an artificially colored target disrupts an operator's visual processing thereby hindering the detection of a target. The purpose of this thesis is to compare the effects of artificial color, natural color, and monochrome formats in visual scene perception. It is hypothesized that participant response times and error rates would be greater at detecting an artificially colored target compared to a natural colored or a target presented achromatically. Two experiments were conducted. Experiment 1 used non-degraded imagery and Experiment 2 used degraded imagery to compare these effects. It was found that reaction time and error rates for naturally colored and achromatic images were similar and substantially less when compared to artificially colored images. For degraded scenes, natural color was more beneficial when compared to achromatic and artificially colored scenes. Additionally, artificially colored scenes caused extremely large error rates and reaction times. These results will provide algorithm developers insight into the importance of color constancy.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF FIGURES

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS

AHPS	Advanced Helicopter Pilotage System
CFH	Color False Hue
CFHS	Color False Hue and Saturation
CFHNOISE	Color False Hue with Noise
CFS	Color False Saturation
CRT	Cathode Ray Tube
FLIR	Forward Looking Infrared Radar
GFH	Gray False Hue
GFHS	Gray False Hue and Saturation
GFHNOISE	Gray False Hue with Noise
GFS	Gray False Saturation
HVS	Human Visual System
I^2	Image Intensifier
IR	Infra-red
MAWTS	Marine Aviation Weapons and Tactics Squadron
NC	Natural Color
NCNOISE	Natural Color with Noise
NG	Natural Gray
NGNOISE	Natural Gray with Noise
NVD	Night Vision Device
NVESD	Night Vision and Electronic Sensors Directorate
SEM	Standard Error of the Mean

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

Recently, military requirements have determined the need to improve existing night vision devices used in military applications. Shortfalls currently exhibited by these operational night vision devices are the lack of target and environment contrast, poor display resolution, inadequate magnification properties and small fields of view. Technology now exists that can provide a modification to existing night vision systems by replacing them with a dual-band color fused sensor. Modifying these systems is more cost effective than the complete replacement. Incorporating the features offered by the dual-band color fused sensor into current military hardware may significantly improve the aforementioned limitations. Extensive research in visual search experiments has demonstrated the utility of sensor fusion; however, the advantages are not clearly defined. It has been determined that color fusion may benefit target detection but hinders a participant's situational awareness. Evaluation provided by various operators have indicated that the lack of color constancy of the fused devices caused the scenes to be aesthetically displeasing.

Vision scientists have long hypothesized that color enhances visual performance in object recognition. Studies have shown that color plays a role in object recognition, but the significance of color has often been debated. Color is commonly used to segment images into regions that contain information about specific objects within the scene. However, it has generally been demonstrated that object recognition is based primarily on the representation of shape and that identification by surface texture and color may therefore be used as secondary cues in identification. With this theory in mind, we must ask why the military would want to incorporate color into existing night vision devices.

Space requirements in military vehicles and aircraft have limited the size of the visual displays. These small displays present imagery that is often blurred or viewed under low light conditions. Images that suffer from this form of degradation lose their visual acuity and edge definition. Research concerning colors role using degraded objects has demonstrated that color is important in object identification. Without defined object contour, color is used to segment objects from their background to facilitate identification.

One significant limitation attributed to night vision fused sensors is that current algorithms are incapable of providing consistent color to objects. This is because information taken from night sensors is normally outside the range of the HVS's sensitivity. Therefore, color is added according to the existing contrast between the object and background temperature differential. The temperature differential dictates the coloring scheme of the object, thereby prohibiting any form of standardization amongst identifying objects by specific colors. However, false coloring algorithms are currently widely used in medical and meteorological displays. These diverse areas have devised color schemes as symbolic measures of significance. With the inability to standardize object color in fused night vision sensors, will color enhance object recognition?

The influence of color was studied as a feature against its influence as stored knowledge in object recognition. Stored knowledge is interpreted as semantic information that explains the prototypical colors of objects, such as the knowledge that apples are typically red or green. Participants respond faster to objects having prototypical colors than objects that do not possess any correlation to the presented color. When objects were viewed in an unnatural scene, participant reaction times increased.

This thesis is designed to validate previous color studies, by using professional photographs with and without degraded edges. It is hypothesized that in high resolution scenes, natural color images will not enhance object recognition when compared to monochromatic images, and non-prototypical (artificial) colored scenes will hinder object recognition. For low-resolution images, natural color will enhance object recognition when compared to monochrome scenes, and artificially color scenes would hinder object recognition.

The results of both experiments confirm the hypothesis. Participant's that viewed high resolution natural colored and monochromatic scenes had similar reaction times and error rates. In the artificially colored scenes, the reaction times and error rates were substantially larger. For low-resolution scenes, natural color significantly enhanced object recognition while artificial color hindered a participant's ability to efficiently recognize the objects. Again, participant error rates paralleled their reaction times. Participants were more efficient when viewing natural color scenes and were significantly inefficient when viewing scenes that did not possess any form of consistent color.

This research has confirmed previous vision studies that included the use of objects being observed in their natural environments instead of against a neutral background. It is recommended that similar vision studies be conducted using imagery taken from color fused sensors instead of commercial imagery to further validate these findings.

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGEMENTS

The author would like to acknowledge and express appreciation to my thesis committee members, Professor "Kip" Krebs and Professor Samuel Buttrey, for their patience in going above and beyond the Operations Research curriculum to teach me the intricacies of vision research and statistical methods the were needed for this thesis.

I would also like to express my appreciation to Dr. Jason McCarley and Dr. Mike Sinai for their guidance and expertise in the field of vision research. Their assistance in providing the programming and ideas to conduct the experiments significantly contributed to my ability to complete the work.

Special thanks to the faculty of the Operations Research curriculum for providing me the knowledge that enabled me to pursue and complete the research required in this field.

Finally, this thesis would not have been possible without the loving support of my wife, Lise, and my children, Zachary and Melissa. Their love, support, sacrifice and encouragement was solely responsible for enabling me to complete the thesis and studies at the Naval Postgraduate School.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

Throughout the history of warfare, nations have pursued methods that helped them gain tactical advantage over the enemy. Many of these methods involved the element of surprise. However, because of advancements in satellite surveillance systems and other forms of innovations in intelligence gathering, the element of surprise has been effectively reduced. A remaining element of warfare that has yet to be fully exploited is the ability to operate under the cover of darkness, or in low visibility. Most intelligence and satellite surveillance systems parallel the human visual system (HVS) in that, they educe reflected light, and as such, are ineffective at night. Therefore, military technology has enunciated the development and refinement of night vision systems that permit forces to operate under the cover of darkness. These systems are commonly referred as Night Vision Devices (NVD's).

The two most common NVD's employed by military forces are the forward-looking infra-red radar (FLIR) and the night vision goggle (NVG). Although their purpose is to expose environmental information in the darkness, they function very differently. FLIR's operate in the infra-red region of the electromagnetic spectrum. They detect thermal differences between an object and its background. The greater the thermal difference, the higher the contrast portrayed in the image. Hence, a major limitation of a FLIR sensor is that it requires a thermal difference to adequately reveal a target that is detectable to a human observer. There are numerous occasions where this limitation may impede night operations. Heavy precipitation and dense foliage tend to create a homogeneous thermal scene. When this occurs, FLIR sensors are superfluous to night operators (MAWTS-1, 1995).

NVG's require reflected radiated light to function. Whether this energy originates from celestial radiated energy or man-made energy, NVG's magnify this energy to illuminate the scene. A major limitation of this device is the requirement of reflected energy. Operations under cloud cover or in dense foliage may severely restrict the devices potential (Wolfe, 1994).

U.S. military forces have successfully employed these devices in combat operations. As recently as in Operation Desert Storm and Bosnia peacekeeping operations, military forces have used NVD's frequently and have conducted extensive night operations safely and effectively (Time-Life Books, 1991). Unfortunately, the widespread proliferation of this technology (Klass, 1994) has permitted other nations to acquire these devices which has reduced the technological superiority of U.S. forces on the battlefield. In order to regain battlefield superiority, the United States is pursuing technology that may enable forces to reacquire this advantage. Some of these advantages may come from improving the existing night vision capability.

Computer technology has permitted the U.S. to consolidate sensory outputs from a combination of different NVD's within a single representation. One such combination consists of fusing the output of the NVG sensor with the output of the FLIR sensor. Individually, each sensor displays unique characteristics of the visual scene. Despite the deficiencies of each sensor, fusing individual sensor outputs into a single representation may potentially overcome individual weaknesses and provide more opportunities to observe the scene under more heterogeneous environmental conditions. For example, in the absence of visible light, an object may still be observed if it possess any form of thermal signature. Although sensor fusion may potentially take advantage of individual

sensor limitations, the output of each sensor is presented in the same monochromatic format that is displayed with individual sensors. Because of this, a lack of background contrast may continue to exist. One possible method of subjugating this lack of background contrast is by introducing color to the display. Color may intensify the context of a scene, thereby permitting the operator more opportunity to efficiently perform his search (Krebs, Scribner, Miller, Ogawa, and Shuler, 1998).

These color fusion algorithms presume that the addition of color to the scene would enhance object detection (Scribner, Warren, Schuler, Satyshur and Kruer, 1998). One significant limitation to providing color to fused images is the inability to reconstruct color constancy. Current computer algorithms provide image colors according to thermal contrast. Because the thermal signature is continuously changing, the inability to control for color constancy is lost. Recent studies comparing the possible benefits of employing color in displays with monochromatic displays have been inconsistent. These studies either failed to show a significant advantage for color over grayscale images or they found the advantage to be scene dependent. Therefore, the research failed to find specific advantages to displaying fused color scenes. (Sampson, Krebs, Scribner, and Essock, 1996; Krebs, et al., 1998; Essock, Sinai, McCarley, Krebs, and DeFord, 1998)

Similar false coloring algorithms are currently being used in medical (Schmidt, Hier, Benyamin, and DeForest, 1988), meteorological (Uttal, Baruch and Allen, 1994), and automotive displays (Krebs, Scribner, Schuler, Miller and Lobek, 1996). These diverse areas have devised color scenes as symbolic measures of significance. For example, the color red displayed on a weather radar screen portrays the existence of severe precipitation whereas the green may signify light precipitation. Research and

training in these fields have standardized these false colors into providing meaningful information to individuals. It is possible that if a similar standardization of color is incorporated in image fusion algorithms, the meaning of specific colors could be learned and therefore proven beneficial.

NVD's are single-band sensors that operate outside the range of the human visual system's sensitivity. They convey no chromatic information. Current artificial color algorithms base their coloring schemes on sensor contrast between the reflective and thermal energy detected from the scene (Krebs, et al., 1998). The objective of artificial color processing is to emphasize sensor contrast rather than reproducing the actual or true colors of the scene. As a result, the "correct" color information of the scene is lost. Furthermore, the sensor contrast differential dictates the coloring scheme of the image, thereby prohibiting the ability to provide standard colors to objects within a scene. Perhaps it is this lack of color standardization that is a contributing factor to the inconclusive results of previous psychophysical fused color studies (Steele and Perconti, 1997).

Basic research on object recognition has determined color to be non-beneficial when compared to grayscale images (Biederman and Ju, 1988). However, this inference has often been debated. Some research has shown that color benefits object recognition while others have not shown any significance. A possible reason for these inconsistencies may arise from the differing experimental methodologies employed by these studies. It may be the type of task performed and the cues that were provided to participants that determined the role of color (Wurm, L.H., Legge, G.E., Isenberg, L.M., and Luebker, A., 1993; Biederman and Ju, 1988; Joseph and Proffitt, 1996). No known

research has attempted to determine colors role using global scenes in object recognition. Therefore, attempting to apply the existing color theories to pseudo-color fused theory may be inappropriate.

A. OBJECTIVE

The objective of this thesis is to clarify the role of natural color and artificial color in natural scene perception. Currently, visual devices in military vehicles are normally small, compact and are often characterized by poor resolution. This may cause imagery to be presented as blurred and lack defined contour information. Under these additions, it might be expected that color would benefit object recognition. This leads us to question the function of color vision, and the role it plays in object recognition, especially if the displayed color does not depict the natural scene.

B. THE RESEARCH QUESTION

A major reason that previous research concerning the role of color in object recognition has been inconclusive may be due to the existing experimental methodologies. The methodologies of previous research ranged from comparing black and white line drawings to colored pictures of manufactured objects (Biederman and Ju, 1988), to comparing natural and artificially colored line drawings of natural objects against neutral backgrounds (Joseph and Proffitt, 1996). It may be concluded that different methodologies may produce varied results. In this thesis, objects will be observed in their natural settings with the intent to compare the effects of natural and artificial color images using professionally photographed images. Once participant performance is known when viewing non-degraded color images, it is expected that the results will adversely differ when viewing degraded images.

C. SCOPE, LIMITATIONS, AND ASSUMPTIONS

For this research, professionally photographed daylight images were used in place of fused images to determine the role of true and artificial color in object recognition. This provided more flexibility in selecting images based upon standards that were set prior to data collection. Although the selected images did not resemble fused imagery from NVD's, the role of true color and artificially colored natural scenes could still be examined. Two experiments were conducted. The first experiment attempted to determine whether artificial color was perceived similarly as monochrome and natural color using non-degraded imagery. Based on previous findings, it is hypothesized that there will be no advantage of color in object recognition, but artificially colored scenes may disrupt the HVS's ability to efficiently perceive objects within the scene. The second experiment attempted to simulate NVD representations using similar commercial images used in the first experiment. However, noise was added to the imagery to approximate the degraded resolution of NVD displays. To validate the research conducted by Biederman and Ju (1988), Joseph and Proffitt (1996) and Wurm, et al., (1993), it is hypothesized that there will be an advantage of color in object recognition and that artificially colored images will disrupt the HVS when observed in degraded conditions. Additionally, given the additional data obtained in the second experiment using different imagery, portions of the findings from the first experiment could be validated.

D. ORGANIZATION OF STUDY

This thesis is organized into five chapters. Chapter I is the introduction, which gives a general description of current limitations to providing color to fused images. Chapter II provides the necessary background information relevant to night vision

technology. It also provides in detail, previous research of the role of color in object recognition. Chapter III and IV describe the methodology used to conduct Experiments 1 and 2 respectively, the procedures used in selecting and manipulating the images, and the experimental design. The chapters also provide data analysis and interpretation of the data collected from both experiments. Chapter V provides conclusions and recommendations for further research.

THIS PAGE INTENTIONALLY LEFT BLANK

II. BACKGROUND

A general historical review of events leading up to the technology that produced these devices should provide the reader with a basic understanding of the problems associated with providing color to NVD's. A general description and characteristics of individual sensors is provided. With knowledge of sensor capabilities and limitations, the characteristics of sensor fusion can be understood. Also, a comprehensive understanding of previous research involving the use of color in object recognition is provided to aid in the development of theories that may help provide answers to the contradictions exhibited in previous color fusion studies.

A. HISTORY

To be successful in warfare, a striking force must maintain an advantage over the adversary (Clausewicz, 1976). Efforts to maintain this advantage have resulted in the development of more destructive weaponry and the creation of more efficient tactics. Although many new technologies were introduced during World War II, American forces did not exploit night combat operations until the latter stages of the war. Until then, night operations were typically utilized for planning subsequent daytime operations and relocating forces for an ensuing battle. Many U.S. forces were lost in combat during daylight hours. It was not until the "Battle at Cape St. George" during the Pacific campaign in World War II, where Captain (later Admiral) Arleigh Burke's forces inflicted heavy damage upon the main Japanese surface forces, that large-scale night tactics were designed and practiced. One of the major contributing factors to Burke's success was his ability to exploit night operations. He recognized this paradigm and prepared his forces by devising and employing tactics that took advantage of the enemy's

inability to respond under these conditions (Potter, 1990).

The Korean War produced no radical changes to combat tactics during night operations. This was partially due to the insufficiency of technical advances of night optical devices, and the fairly limited understanding that researchers had of human visual processing. However, since then, the infra-red industry has expanded rapidly. This industrial development was motivated by the inability of U.S. forces to expostulate North Vietnamese forces from conducting night operations against isolated outposts, force resupply, or moving logistics (Schwarzkopf, 1992). Since the post Vietnam era, virtually all military high value platforms possess infra-red imaging capability. The vast investment in NVD's by the military services and law enforcement agencies has spawned an enormous industrial community dedicated not only to the manufacture of the devices, but also to their large-scale integration into weapons, ships and combat vehicles. As a result, researchers who analyze, measure and predict the performance of NVD's have grown from a small community, intimately involved and thoroughly familiar with the technology and its theory, to an extremely diverse population of engineers, managers and scientists. The necessity to see "into the night" is the driving force in the development of NVD's (Berry, 1993).

There are numerous night vision enhancement systems in the U.S. armed forces' inventory. Every system is capable of functioning beyond the HVS's unaided capability. These systems have been proven effective in a myriad of diverse combat operations. However, unanticipated problems have arisen while utilizing these devises. A human's unaided perception of the surroundings at night is vastly different when observed with NVD's. The user's lack of understanding of the night environment and its impact on the

NVD's performance has caused the capabilities of these devices to be exceeded, resulting in numerous mishaps (Salvendy, 1997).

Currently, almost all military personnel have trained with or have been exposed to NVD's. With the radical change in military budgets and huge reduction of forces, the exploitation of night operations allows U.S. military forces to do "more with less" while retaining the combat advantage over enemy forces. As recently seen in Operation Desert Storm, many of U.S. military campaigns occurred at night. Coalition forces exposed Iraqi forces to a "24 hour battlefield" by employing NVD tactics; a strategy the Iraqi forces were ill prepared to confront. U.S. forces easily demonstrated the ability to conduct sophisticated and coordinated operations with the aid of these devices on their platforms (Schwarzkopf, 1992). A brief overview of the NVD's is presented to provide the reader with a basic understanding of these devices. A more detailed coverage of the theory and operation of NVD's is provided in MAWTS-1 (1994).

B. IMAGE INTENSIFIERS (NVG'S)

NVG's operate in the near visible and near infra-red (IR) spectrum (wavelengths of 570-900 nanometers) and depend entirely on reflected energy (Figure 1).

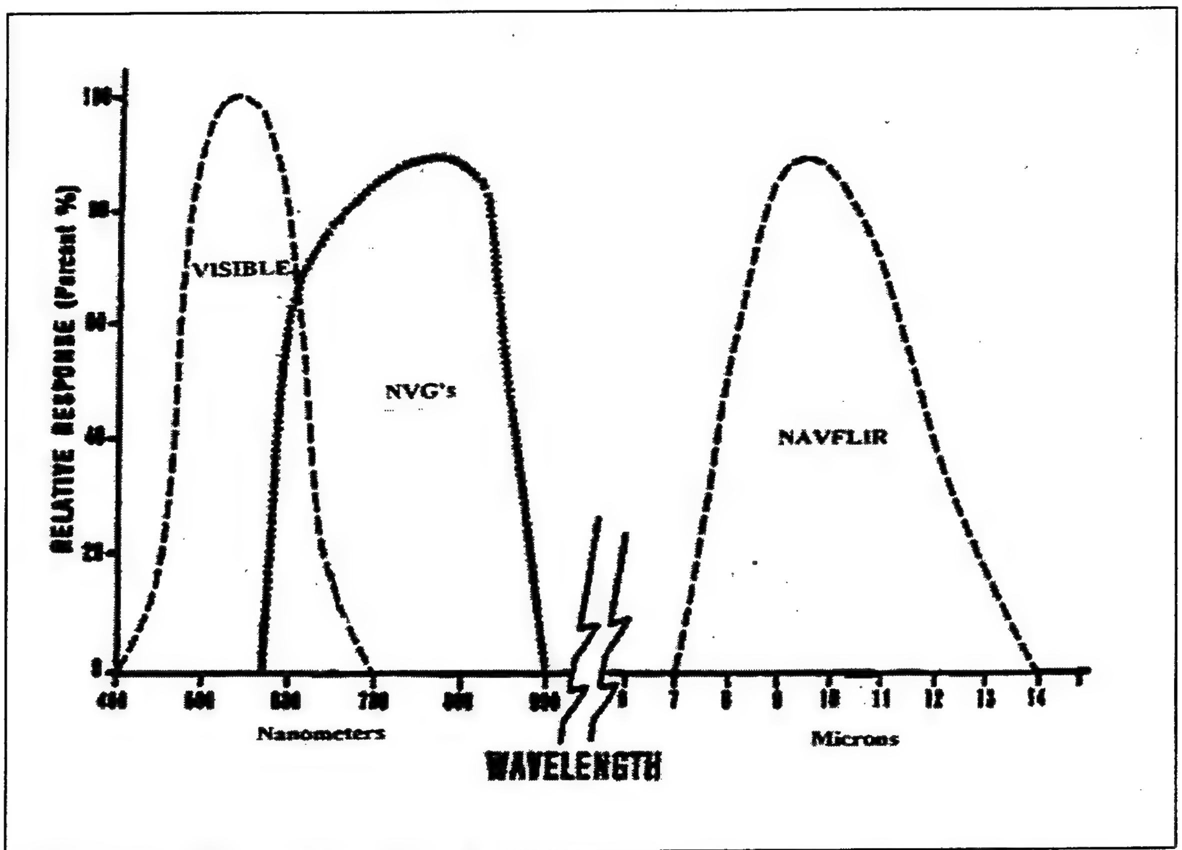


Figure 1: The portions of the electromagnetic spectrum used in unaided human vision, NVG's and FLIR's. (MAWTS-1, 1995)

The first generation NVG's relied entirely on light at visible wavelengths, but the third generation (GEN-III) instruments make use of infra-red light just beyond the visible spectrum (NVESD, 1997). Current NVG technology centers on the GEN-III devices. Even on the darkest of nights when visible light is practically non-existent, infra-red energy is still plentiful. Additionally, the reflective characteristics of different surfaces are more pronounced in the infra-red band, thus creating an image displayed with greater contrast (Time-Life Books, 1991).

The two sources of light that enhance the HVS aided by NVG's are reflected and generated light. Reflected light normally originates from energy emitted by celestial bodies such as the moon or stars that is reflected off an object's surface. Generated light

originates from artificial sources of illumination such as city lights and shipboard lights. A specific characteristic of NVG's is that with proper ambient light levels, the visual clarity is superb. There are several variables that affect the optimal performance of NVG's. These variables include the amount of illumination within the scene, characteristics of the terrain, and atmospheric conditions in which the sensor is operating (FM 34-81-1, 1992). Atmospheric conditions have the greatest impact on NVG effectiveness. The dominant atmospheric factor that affects NVG performance is the quantity of water vapor (humidity) present. This is because water molecules in the air absorb and reflect light from the intended source (FM 34-81-1, 1992). A sample image viewed with a NVG is shown in Figure 2.

Figure 2: Sample image taken with a NVG. Notice the clarity of the objects. (A.P.Hill, 1998)

C. THERMAL SENSORS (FLIR)

FLIR's are electronic devices that convert invisible thermal energy into a visible image. FLIR's operate in the 7-14 micron wavelength band of the electromagnetic

spectrum (Figure 1). FLIR technology is based on the detection of emitted and reflected thermal energy. FLIR's operate as differential temperature measuring systems, in that, a measurable temperature difference must exist between an object and the background in which the sensor operates. This measurement is referred to as "DELTA T" (Schlessinger, 1995).

The infra-red signatures of targets and backgrounds are far more complex than the visible signatures in NVG's because emission has virtually no influence (NVESD, 1997). As complex as infrared signatures are, the limited scientific capabilities at the disposal of the FLIR community cannot cope with anything beyond the simplest expression of target and background signature. The predominant analysis in thermal theory is currently based on the assumption that an object behaves like a blackbody at a temperature some number of degrees different from a uniform blackbody background, such as the environment in which the object is viewed (Campana, 1993).

The two general types of sources that enable FLIR devices to function are thermal and selective radiated thermal energy. Thermal sources, such as the sun or combustible engine, radiate over a wide frequency spectrum with the maximum radiated energy level concentrated at a particular frequency. Selective thermal sources generally concentrate on a very narrow frequency band. An example of selective thermal radiation is a laser beam (Steele and Perconti, 1997).

The diurnal cycle is a measure of the rate at which objects and their backgrounds heat and cool. Large dense objects tend to heat and cool slowly, whereas, less dense objects such as trees and grass, heat and cool more rapidly. Objects heated by sunlight are the mechanism through which the diurnal cycle drives thermal signatures (Shumaker,

Wood, and Thacker, 1988). The rate of change in temperature of a surface is dependent not only on its emissivity but also on its shape, size, heating capacity, conductivity and convective cooling/heating effects (Wolfe, 1996).

Sometimes, the radiated temperature of an object matches the temperature of the surrounding environment resulting in a Delta T = 0. On hot days, an object normally fails to reach the evening background temperature before the sun rises again to restore the heat cycle. As the sun rises, the cooler background warms up rapidly and soon exceeds the target temperature. Twice in a 24-hour period, Delta T goes below zero. From sunrise to late afternoon, the background temperature is generally greater than the object temperature thereby masking the objects thermal effect on a FLIR device (FM 34-81-1, 1992). (See Figure 3)

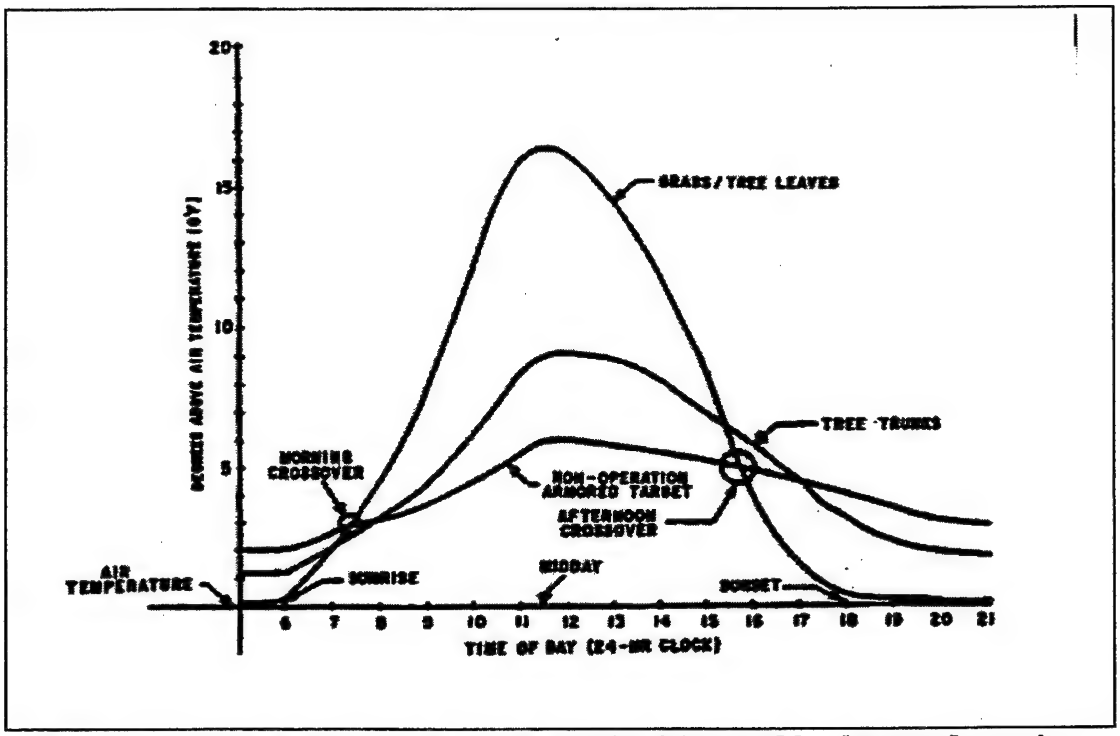


Figure 3: The Diurnal cycle for a man-made object and background terrain. Crossover times are also shown (MAWTS-1, 1994)

Atmospheric conditions also have a very profound effect on the effectiveness of

FLIR's. The two predominate atmospheric factors are energy absorption and scattering. Thermal absorption in the atmosphere is a greater concern that contributes to thermal signature loss and scatter (MAWTS-1, 1994). A characteristic of FLIR representation is the amount of contrast level between objects and backgrounds. This contrast dictates the resolution of the display. A sample image viewed with a FLIR is shown in Figure 4.

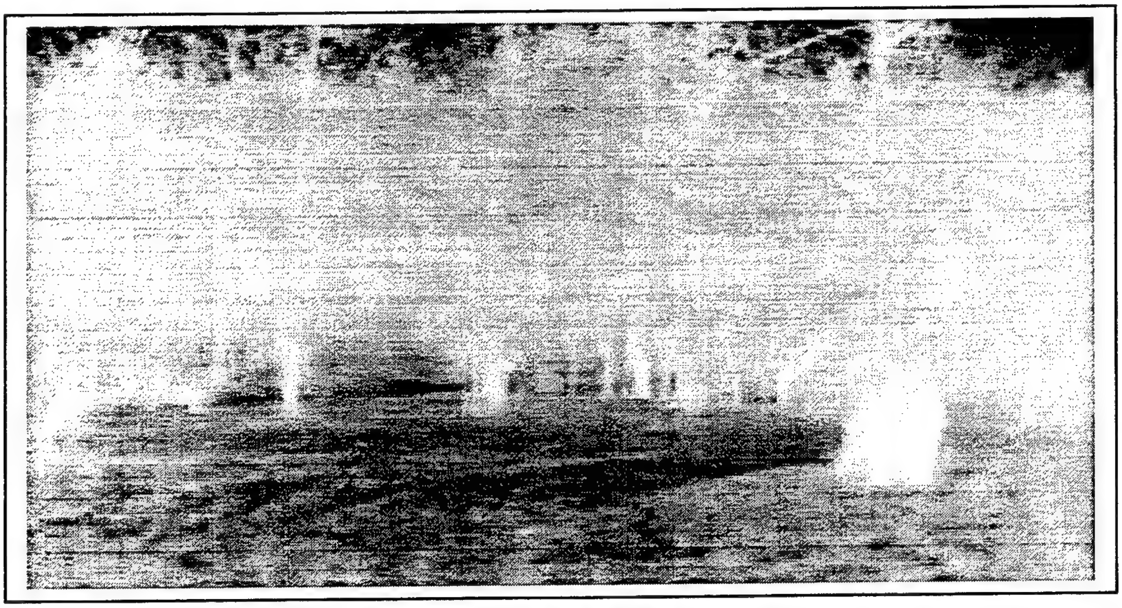


Figure 4: Sample image taken with a FLIR. Notice the brightness and poorer resolution of the objects. (A.P.Hill, 1998)

Current FLIR technology is centered on first generation (GEN-I) FLIR devices. The U.S. Army began integration of second generation FLIR's into new and existing weapon systems to maximize U.S. forces advantage on the battlefield. The center piece of this system is a common subsystem that is currently being produced for the Abrams Tank, Bradley Fighting Vehicle, and Long Range Advanced Scout Sensor System (NVESD, 1997).

D. FUSED SENSORS

Improvements to individual NVD's have provided substantial increases in sensor detection ranges and display resolution. However, these improvements cannot avoid the

limitations of the electromagnetic spectrum. Each sensor suffers from its own limitations. NVG's must have reflected light for detection and FLIR's must be able to detect a contrast in thermal energy between an object and the background. Scene analysis by an operator may potentially benefit from a fused representation (combined FLIR and NVG) of a scene taken in different spectral bands. For example, following a period of extensive cooling such as a rain shower, the visible bands may represent the background in great detail whereas the infra-red bands that represent the scene may be negligible or provide a representation of the scene that is severely degraded due to the low thermal contrast. Also, a target that is camouflaged for visible detection may not be detected in the visible bands, but may be clearly represented in the infra-red bands by providing a thermal contrast between the object and background. The fusion of visible and thermal imagery on a single display may allow both target detection, provided by the thermal image with respect to the context, and unambiguous target localization, provided by the visible image (Toet, IJspeert, Waxman, and Aguilar, 1997). Technology now exists that enables information provided by these sensors to be combined and represented on a single display.

The basis for fusing multiple sensors originated from the notion that pit vipers incorporate a similar concept. Various species of pit vipers combine the attributes of visible and infra-red vision for hunting at night with little or no visible light. The snake's visual system is composed of infra-red sensors and pit organs, located near the head, that open below and in front of the eyes. Infra-red information is sensed by the snake's pit organs and is then sent to the brain, where it is combined with visible information obtained by the snakes eyes (Hartline and Newman, 1982). This combined information

allows the pit viper to hunt efficiently in daytime as well as at night. Although the pit viper can strike with deadly accuracy on just the thermal signature of the prey, mapping of neurological impulses in the brain show that the visual and infra-red spectrum are combined (fused) to provide a complete picture of the scene (Hartline and Newman, 1982).

Having the capability to combine multiple NVD's contained in military equipment, ongoing research is being conducted to attempt to develop an optimum multi-sensor integration suite (Campana, 1993). Some advantages of combining multiple spectrums into a single representation might be:

- Reduced cost, space, and weight requirements from combined resources.
- Reduced operator workload by eliminating the need to alternate between two sensors.
- Improved object search, detection, and recognition.

One of the characteristics of the HVS is its ability to process color efficiently (Jayle, Ourgurd, Baisinger, Holmes and Duke-Elder, 1959). Presenting displays in monochromatic format, such as the displays of NVD's, restricts the capability to optimally utilize the HVS. If the HVS were monochromatic, scenes would be similar to those displayed on a cathode-ray tube (CRT), where digitized monochromatic images physically represent each pixel as one of 256 different levels of brightness (gray-levels) (Waxman, Fay, Gove, Seibert, Racamato, Carrick, and Savoye, 1995). However, the HVS can perceptually distinguish only about 100 different gray levels on a CRT with images collected under ideal lighting conditions (Scribner, et al., 1998). For images collected under dim light, the gray-scale depth of the image is even more limited (Toet and Walraven, 1996). To improve the probability of detecting an object within a scene,

combining multiple bands into a single fused color scene should enhance the contrast between the foreground and background objects in the scene (Scribner, Satyshur and Kruer, 1993). Figure 5 shows an example of an image viewed under fused color.

Figure 5: Sample image taken with fused sensors (A.P.Hill, 1998).

Besides the advantages already discussed of displaying fused sensors on a single representation, fusion also provides the opportunity for the presentation of imagery on chromatic displays. However, color imaging is only possible when the responses of the fused sensors differ in spectral sensitivity (Krebs, et al., 1998).

It is important to understand the distinction between a color scene observed by the unaided eye through the human observer and a processed pseudo-color scene. Psychologically, certain colors have developed meaning with time. Red for instance, possesses an instinctive psychological impact that tends to draw attention, enhances detection and discriminates possible dangers (Valdez and Mehrabian, 1994). In order to ensure that these color cues appear the same for a wide range of environments throughout the day, the visual system adapted the ability to distinguish these colors under varying natural lighting conditions (Sekuler and Blake, 1994).

The spectral composition of light impinging on the HVS sensory receptors is determined by the spectral composition of the luminance and the intensity of the energy of an object's surface reflection. The intensity of the reflected light is extremely inconsistent, varying due to factors such as time-of-day effects, atmospheric conditions, and the amount of airborne particles in the air. This lack of consistency for the intensity of reflected light required the HVS to develop a variety of mechanisms to disentangle the contradictions of varying lumination and thereby to achieve nearly constant color perception based on distal surface reflectivity (Matlin and Foley, 1997). A major limitation to sensor fusion systems is that these mechanisms cannot be duplicated to achieve the same constant color perception. Sensor fusion systems produce color mappings that vary with changes in the intensity of light's spectral composition. The potential disadvantage caused by the variability in spectral illumination may be magnified by the relatively arbitrary color mappings produced by this new technology. This result is due to the spectral sensitivity channels that compose sensor fusion technology that do not correspond to the trichromatic channels of the HVS. This causes the color mapping produced by fused sensors to be unnatural in appearance (Krebs, 1998). Before proceeding with a discussion on previous natural and false color studies, a more detailed description of color vision may aid in understanding the difficulties in relating false color to natural color.

E. HUMAN VISUAL SYSTEM

The HVS is an extremely complicated system. It is made up of two separate but inter-related systems; the eye (receptor) and the optic neural pathways (processors) (Legrand, 1968). The sensory receptors in the eye are sensitive to energy within a limited range of the electromagnetic spectrum, specifically, wavelengths from approximately 0.4

to 0.7 microns. Figure 6 depicts the electromagnetic spectrum. Any energy beyond this range will not be visually detected because it has no effect on the receptors (Sekular and Blake, 1994).

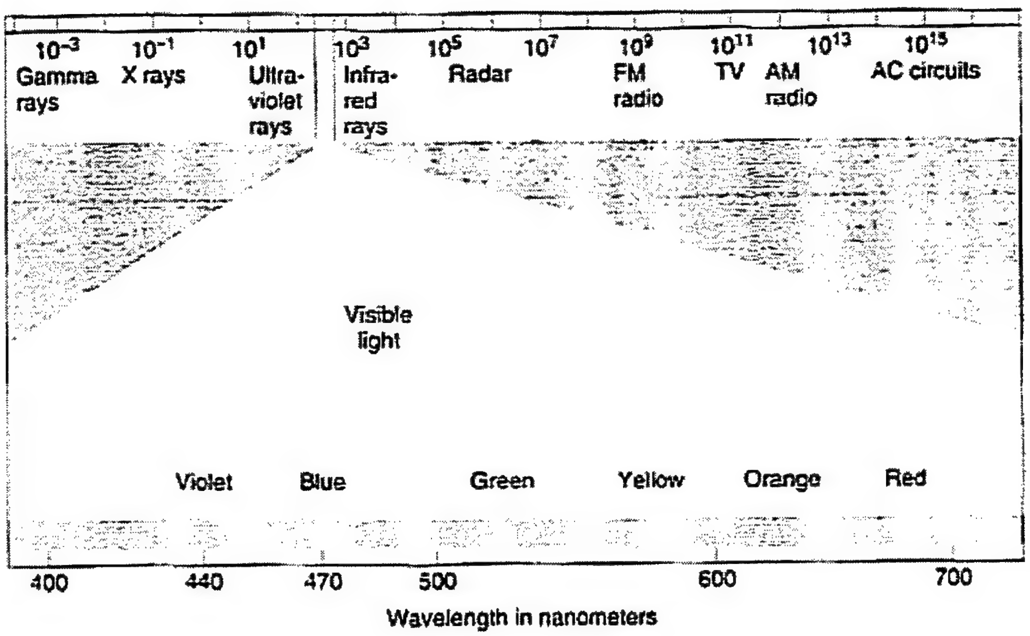


Figure 6: The electromagnetic spectrum. (Matlin and Foley, 1997)

Visual processing is accomplished by a system of neurological pathways between the retina and the brain that convert the reflected light energy into images. A more detailed description can be found in textbooks on vision (Sekular and Blake, 1994).

The retina is the interface between perception and reception in the eye. It contains two major types of photoreceptor cells called rods and cones. Rods are primarily involved in vision under very low levels of light. They are slow acting, provide minimal visual clarity, and cannot discern color. Rod vision is also referred to as scoptic vision (Sheppard, 1968). There are three sub-types of cone cells that are fast acting, sense the entire visual color spectrum, and provide maximum clarity, but function poorly

during low light conditions. Cone vision is also referred to as photopic vision (Legrand, 1968).

Each photoreceptor cell is coated with a chemical substance called photopigments that accomplish the transduction of light. For the three sub-types of cone cells, each photopigment absorbs more light in one portion of the electromagnetic spectrum than in any other area (Matlin and Foley, 1997). Estimates of the portions of the electromagnetic spectrum that are absorbed by the cone cells are shown in Figure 7.

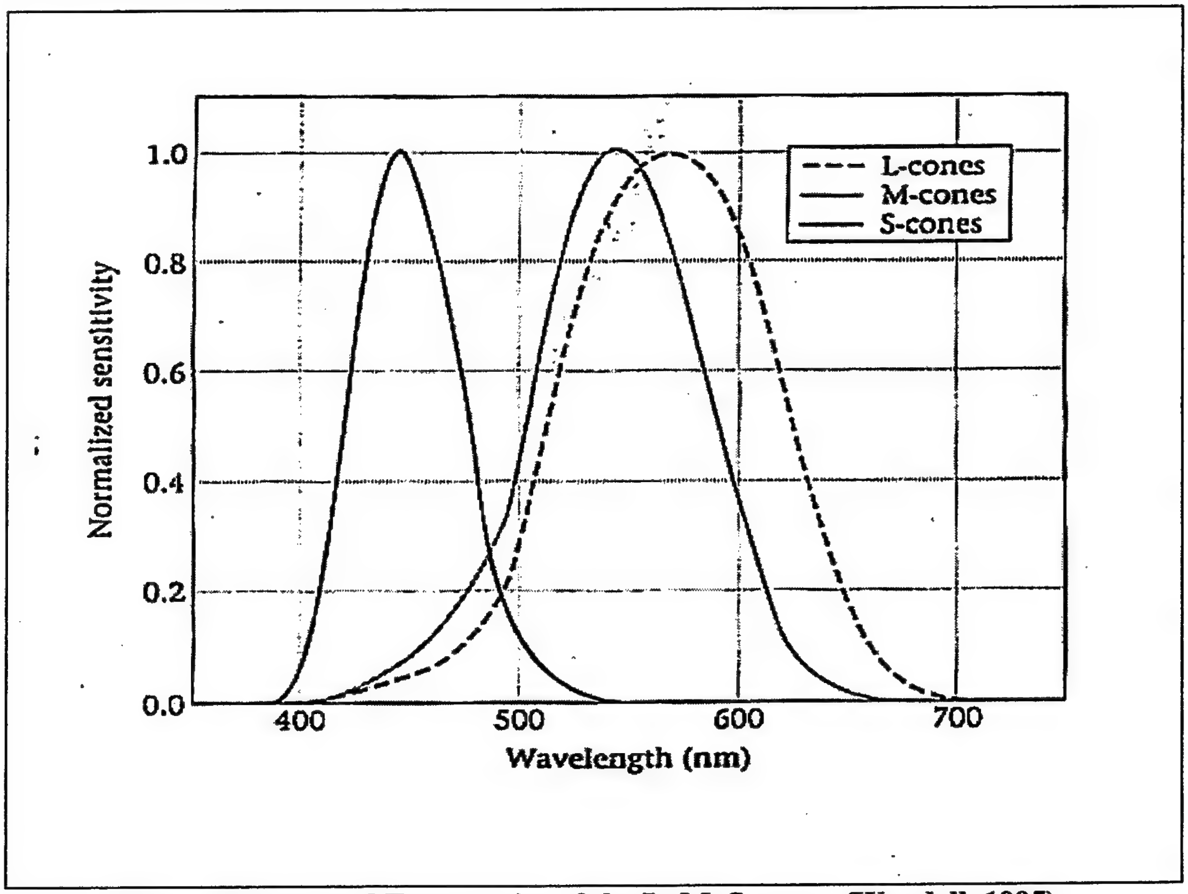


Figure 7: Spectral Frequencies of the L, M, S cones. (Wandell, 1995)

As seen in Figure 7, each particular cone cell is referred to as the S-cones (shortwave), M-cones (mediumwave) and L-cones (longwave) and each corresponds to a particular color with the color spectrum, blue, green and red, respectively (Wandall,

1995).

The spectral properties of light are measured in terms of the amount of energy emitted at each wavelength, namely the spectral power distribution of the light source. The portion of light that is reflected off an object's surface defines the surface-reflectance function. This reflected energy leads to different amounts of absorption in the three cone classes and it is this interpretation of cone absorption that is the basis of color perception. Therefore, the light incident to the HVS is a function of the spectral power distribution of the ambient illumination and the surface-reflectance function (Wandall, 1995). For example, suppose that the eye was presented a target color (orange) of 600-nanometer wavelength. From Figure 7, the target would present a large amount of absorption in both the M-cones and L-cones and the color would consist of a mixture of L-cones (red) and a lesser amount of M-cones (green) that produces the color orange. The remaining portions of the reflected energy are absorbed by the object, prohibiting the receptors from receiving energy within the specific frequency bands (Matlin and Foley, 1997).

Isaac Newton demonstrated in the late 17th century that white light consists of a combination of different colored lights that are evenly distributed across the visible electromagnetic frequency spectrum (Matlin and Foley, 1997). Figure 8 shows the primary colors and associated wavelengths in relation to the electromagnetic spectrum.

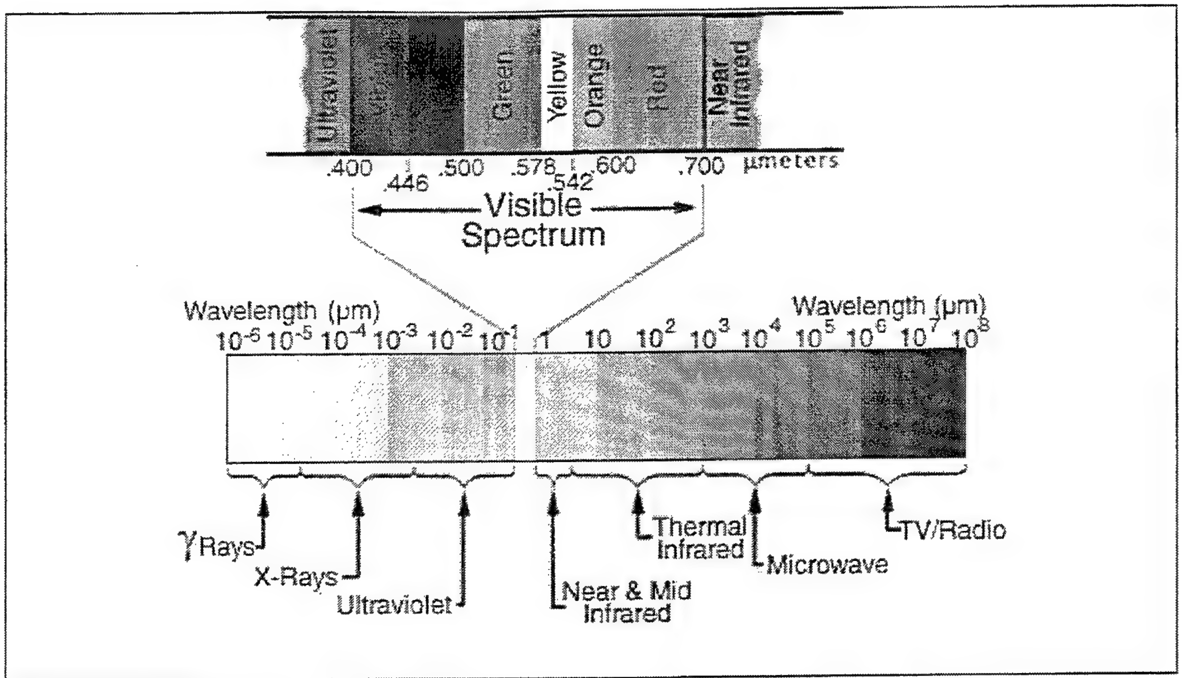


Figure 8: Visible Color Spectrum (Matlin and Foley, 1997)

It is difficult to imagine that objects may look as though they are colored when in fact, they are actually reflecting light from the unabsorbed portions of the spectrum. A chair may appear blue, but in reality it is blue because its surface is absorbing most of the medium and long wavelengths and is primarily reflecting the wavelengths from the blue portion of the spectrum to the HVS. Since the S-cones would absorb the majority of the energy and the L-cones and M-cones absorption rates may be negligible, the object would be perceived as blue in color (Matlin and Foley, 1997).

Another characteristic of color is color constancy. In color constancy, the HVS tends to see the same colors during varying levels of illumination. This is because as the illumination changes, the sensitivity distribution of a light source will change at a similar rate across the visible frequency spectrum. The distribution of wavelengths reaching the photopigments of the cones will receive the same information, except at a different intensity. This explains why grass appears to be green on a bright sunny day and on a

cloudy rainy day (Sekular and Blake, 1994).

Light is organized by its wavelength characteristics. As Isaac Newton demonstrated, white light that enters a prism is broken into numerous color components. A method of organizing all the wavelengths of the visible spectrum is accomplished by placing them in a circular position, or color wheel. Figure 9 shows the standard color wheel and distribution of frequencies (Matlin and Foley, 1997).

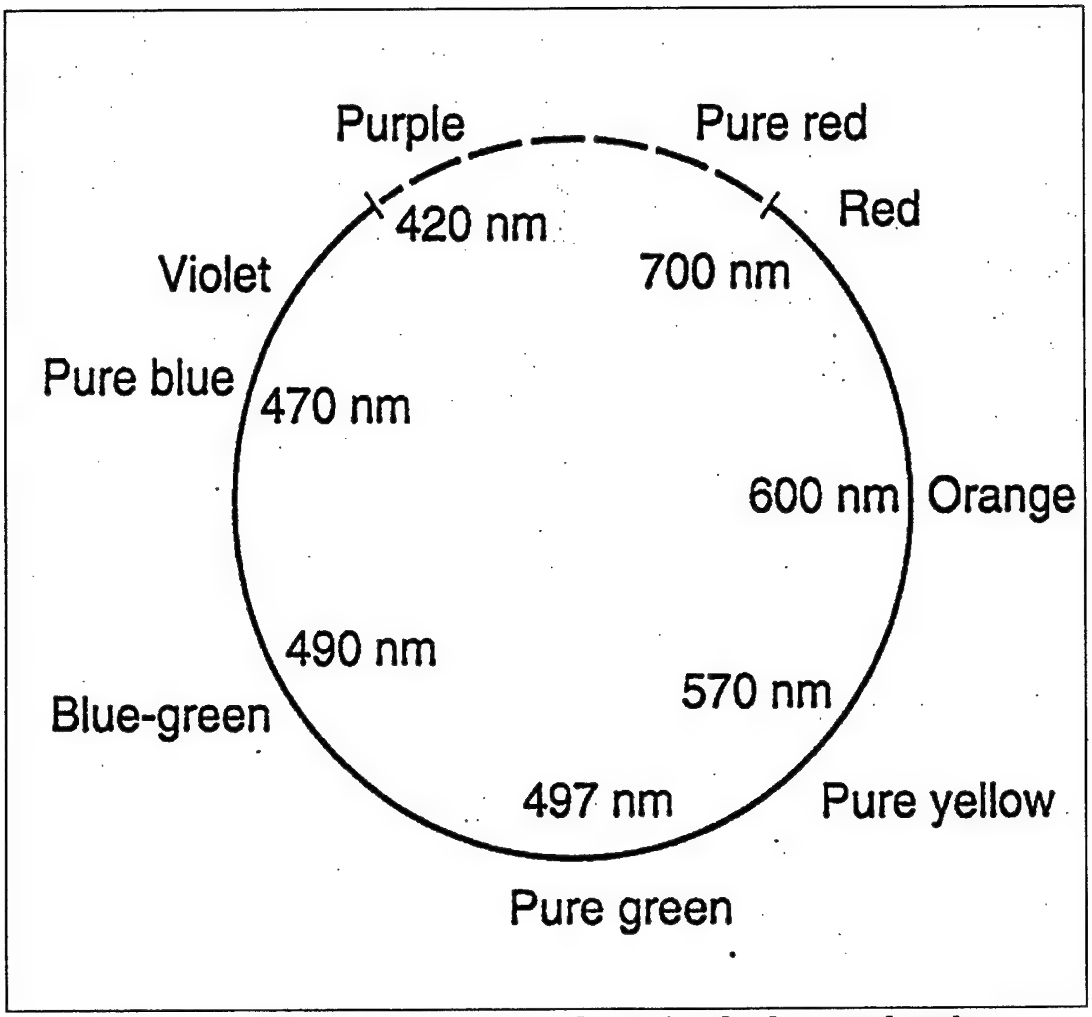


Figure 9: Standard color wheel and associated color wavelengths. (Matlin and Foley, 1995)

Color is also characterized by the amount of saturation that is present. A light that occupies a very narrow frequency band is said to be pure and highly saturated. An

example would be that of a laser beam. Saturation measures the purity of color. As the width of the frequency band of the light expands, additional variants of color are added as they are received through the respective cone cells and the representation is not as pure. Saturation can also be measured on the color wheel. A totally saturated color is displayed on the outside edge of the color wheel and unsaturated color is displayed as the wavelength approaches the color wheel origin. Saturation is only possible when the brightness is intermediate, neither too light nor too dark (Wandall, 1995). Now that an overview of the characteristics of color and the HVS has been presented, we can now discuss color's role in object recognition.

F. REVIEW OF THE LITERATURE

The role of color and its impact on the human perceptual system has intrigued vision researchers for many years. Until recently, color has been attributed to object recognition, in that it was assumed that color aided an individual's ability to recognize objects (Wurm, et al., 1993). Early studies suggest that color vision evolved in early humans to facilitate the search and recognition of food (Polyak, 1957). However, it has since been shown that individuals who possess a color deficiency (color blindness) only become aware of this deficiency after taking a color test (Steward and Cole, 1989). These individuals lead a normal life and function without visual impairment. This leads us to question the function of color vision, and the role it plays in object recognition. Although no firm conclusion exists concerning the role of color in object recognition, most vision researchers agree that color is significant.

Three tasks have typically been used to determine colors role in object recognition. These tasks are classification, verification and naming. Research has shown that although color does not influence classification or verification performance, it does

influence naming performance (Joseph and Proffitt, 1996). However, it will be later shown, that this statement is often debated. For purposes of this thesis, classification is defined as objects that belong to a specific category, such as objects that are either living or non-living (Davidoff and Ostergaard, 1988). In verification tasks, individuals are tasked to validate the relationship between a word and a picture. If an image of an apple was presented to a participant, the participant must respond whether the associated word or phrase matched the presented object (Biederman and Ju, 1988).

Biederman and Ju (1988), conducted a significant study on the role of color in object recognition. This study compared colored pictures of manmade objects to black and white line drawings of the same objects. The objects and line drawings were presented in two kinds of tasks. The first task was a naming task. Participants saw a slide of an object that was presented in either a color photograph or line drawing depiction. Upon recognizing the object, participants named the object using a voice key that recorded reaction times and error rates. It was expected that participant reaction times and error rates for the naming task would be smaller for objects depicted in color format (Biederman and Ju, 1988). The other task was a verification task. Participants had to verify the name of an object by matching it to the image representation. This was accomplished by pressing a YES or NO response on a microswitch. Each presentation was shown in one of three different exposure times followed by a mask. The exposure times were 50, 65 and 100 milliseconds in duration. It was assumed that longer exposure duration and slightly dimmer projector intensity would favor colored photography (Biederman and Ju, 1988).

The results of the experiments were surprising. In the naming tasks in which the

projector intensity was varied and a mask that immediately followed an image presentation was presented randomly, no significant advantages for participant reaction times and error rates for the color images were shown. An astonishing finding during the naming task portion of the experiment was that reaction times were generally larger for images displayed in line drawings when observed with smaller exposure times. This suggests that the HVS may respond less efficiently to colored images when the images are presented momentarily (Biederman and Ju, 1988).

The same color photographs and line drawings were used in the verification task experiment. Participants were given a verbal one-word description of a target and were then instructed to respond once an image was presented. This task enabled the participants to form a mental representation of the target and to also anticipate its texture and details. The results of the verification tasks mirrored the results of the naming task. No advantage for identifying a colored picture over a similar black and white outline was found (Biederman and Ju, 1988).

The researchers concluded that simple line drawings can be identified as quickly and accurately as fully detailed, textured, colored pictures of the same object. These results support the premise that initial access to a mental representation of an object can be modeled by matching the edge-based depiction of the object. Therefore, when an object's edge can be perceived by the HVS, color plays only a secondary role in the real-time recognition of the object (Biederman and Ju, 1988).

To parallel Biederman and Ju's research, another group of visual scientists conducted a similar experiment investigating the role of color in categorical judgements. Line drawings were also used for the experiments. Colored and black-and-white

transparencies were produced for each object that was shown to the participants. The objects were rated according to size (small, smaller, large, and larger) compared to a trumpet, which was defined as the size standard. Additionally, objects were categorized into living and non-living categories. Participants were tasked to verbally indicate the specific categories in which the objects belonged. For example, a color presentation of an airplane would be placed in the "much larger, non-living" category. Assuming that color would have no influence on participant reaction time in the task, the researchers were interested in investigating color benefits on image size and recognition categories. For example, would a participant recognize a colored depiction of a butterfly or an airplane faster when compared to the same pictorial representation in achromatic format (Davidoff and Ostergaard, 1988)?

The results of the experiment showed that color affected neither size nor living/non-living classifications. Although color reduced participant reaction times when compared to reaction times of monochrome images, the results were not significant. The authors speculated that the slightly smaller reaction times for the colored pictures might have been attributed to a color brightness advantage (Davidoff and Ostergaard, 1988).

In a subsequent experiment, identical images were used and participants were tasked to name the viewed objects instead of rating them for object size. This procedure attempted to determine the relationship of color and naming living and non-living objects. Non-living objects typically are not normally associated with a particular color and therefore it was hypothesized that the color advantage would enhance living object recognition better than non-living object recognition. Previous studies (Davidoff and Ostergaard, 1985) indicated that color may be beneficial in object naming but not in

object recognition. Their findings however, were based on an inadequate image sample size. Therefore, the focus of this naming task was to validate previous findings with large image sample sizes. The findings of the research indicated that color did not significantly enhance participant reaction time between living and non-living conditions. It did have a positive effect on participant's reaction times and supported the previous object recognition research but the advantage was found to be not significant. It was concluded that color played a role in object naming but has no effect in object recognition (Davidoff and Ostergaard, 1988). This conclusion contradicts Biederman and Ju's studies that used similar procedures, but different types of pictures. A factor not controlled and a possible contention for these inconsistent results was speculated to be the failure of Biederman and Ju to control luminance characteristics. It was suggested that visual analysis of the color images may have been at a starting disadvantage because of greater limitations in edge extraction compared to the line drawings (Wurm, et al., 1993).

Price and Humphries (1989) examined the effects of color congruency and photographic detail on naming and classification of structurally similar and dissimilar objects. Using the notion that color does not influence object recognition with edge-based effects (Biederman and Ju, 1988), they wanted to determine if these theories could be applied to surface-based effects. Surface-based effects predict that it will benefit object recognition if the effects are shown in conjunction with their surface details, such as a variation in luminance, brightness, texture and color. To determine these effects, the authors conducted a series of experiments in which participants performed subordinate naming and classification tasks using structurally similar and dissimilar objects. Items such as birds were observed with structurally similar shapes and tools for instance, were

presented with structurally dissimilar shapes. Price and Humphries hypothesized that object color and surface detail would be beneficial for discriminating between categorical members. They felt that classification of objects could proceed directly from the structural description of the object. Their findings supported the hypothesis and revealed that surface color benefits not only a naming task but also applies to classification tasks when shape information is not sufficient for discriminating between category members. They also suggested that surface color is more likely to be important for specific categories of objects, namely natural categories, as opposed to artifactual categories. It was therefore concluded that the effects of color were stronger for categories with structurally similar characteristics. This is because naming an object requires finer within-category differentiation. The finer the required differentiation, the stronger the effects of surface detail (Price and Humphries, 1989).

Wurm, Legge, Isenberg, and Luebker (1993) questioned color's role in object recognition using participants who had normal and degraded color vision. They believed that color and shape information interacted in object recognition, especially when spatial resolution was degraded. They also hypothesized that color would improve object recognition for individuals with degraded visual acuity. Previous findings indicated that color had no practical advantage for low visual reading, but the lack of research on low vision object recognition prevented the correlation between color's involvement in reading with object recognition (Wurm, et al., 1993).

The authors chose food items as objects for viewing. This was because using man-made objects, such as those used in prior research, possessed stereotypical shapes. Food objects tend to have a wide range of color and shape representation. For example,

an apple may be red, green or yellow, and may be whole, sliced or bitten. The authors speculated that the reason for the inconsistent findings in previous recognition studies was that luminance was not controlled between the chromatic and achromatic imagery. The authors eliminated any effect of luminance prior to conducting the experiment. Participants were shown 84 images (21 items in four different poses) in one of four different formats. These formats were both blurred color and monochrome and unblurred color and monochrome. Using a naming task, participants were required to rapidly name the food item shown. There were two major findings from the results. First, color did improve the recognition of food objects and second, an interaction between color and spatial resolution did not exist. This implies that color appears to improve object recognition equally for both blurred and unblurred targets (Wurm, et al., 1993).

Next, the authors tested the vision deficient participants. Each participant was categorized according to specific visual impairment. The participants were tasked to view each of the 21 food items in four different poses for a total of 84 different presentations. The images were magnified by a factor of two to facilitate viewing. Each participant equally viewed images in either a color or achromatic representation. The authors hypothesized that color would benefit participants with visual deficiencies in object recognition (Wurm, et al., 1993).

Although participant reaction times for identifying images viewed in color was half that of images viewed in monochrome, statistical analysis failed to show significance. These results were probably due to the large variability of the data due to the heterogeneity of the different visual disorders. The authors concluded that color enhances object recognition for people with low color vision, but object recognition is

hindered by poor visual acuity. They also found that color and visual acuity acted independently in low vision object recognition (Wurm, et al., 1993).

Finally, the authors attempted to determine the relationship of color and prototypical images. Prototypical images were defined as objects that possessed a typical color and shape. Each of the objects was ranked for prototypically. It must be clarified that prototypical objects are much different than objects with diagnostic colors. While the color red may be prototypically associated with an apple, it is also associated with numerous other objects such as tomatoes and cherries. However, orange is associated with relatively few objects, namely carrots and pumpkins, that are identified by their distinctive profiles. Two factors must be present to determine when color is diagnostic. First, the color must be symptomatic of the object (i.e. green is a symptom of spinach), and the other objects presented in the allowable domain should not be of this color. Therefore, since other foods in the experiment were also green, green was not "diagnostic" of spinach (Wurm, et al., 1993). It was expected that object reaction times would be smaller for the most prototypical images. This was because prototypical images may be recognized faster because they contain certain shape characteristics that are stored in memory. Since less prototypical images may have less defined shape attributes, it is expected that the advantage of color increased indirectly with prototypical images. Participants were asked to estimate probabilities of the food categories given a specific color. The results suggested that the participant's knowledge about the color of the food item did not account for the advantage of color in object recognition. To conclude the experiments findings, the authors found that color improved object recognition but the mechanism was sensory rather than cognitive (Wurm, et al., 1993).

Joseph and Proffitt (1996) conducted a series of experiments to determine semantic versus perceptual influences of color in object recognition. They theorized that a significant reason for the contradictory results of previous research was that stored and surface color knowledge must play a role in recognition tasks. Surface knowledge is defined as the depicted color that represents the surface of the object, such as the color yellow for a banana. However, surface color can be arbitrary because an object can be represented by any color. Stored color knowledge is the semantic information about the prototypical colors of objects, such as the knowledge that bananas are typically yellow. Stored color knowledge is not arbitrary because people have shared ideas about the typical colors of objects (Joseph and Proffitt, 1996). The authors felt that an objects surface color must be compared to the activated prototypical color of the image for recognition. The basis for their research was to determine whether the decision that two objects were the same depends on the activation of stored color knowledge or on the processing of surface color (Joseph and Proffitt, 1996).

Using a series of experiments in which they tested the effects of surface color; the effects of stored knowledge; and the effects of combined surface and stored knowledge in verification tasks, they found that congruent color knowledge (red apples) made verification easier than incongruent (purple apples) surface color. Although these results conflicted with Biederman and Ju (1988) findings, they contributed these results to objects used in the imagery. It was assumed that natural objects have stronger associations with colors than artifactual objects. Therefore, the use of surface color as a cue was more beneficial for object recognition from natural categories (Joseph and Proffitt, 1996). They also found that stored color knowledge enhanced object

recognition. When both image and word stimuli were similar by shape and prototypical color, more interference occurred when compared to stimuli that were similar by only shape. When they compared stored and surface color information for object recognition, they found that stored color knowledge had a more profound influence than surface color knowledge (Joseph and Proffitt, 1996).

Obviously, the effects that contributed to the inconsistent results were primarily due to the experimental methodologies used to conduct each task. It appears that color has no influence when viewing artifactual images because prototypical effects are not pronounced. Additionally, presenting a label prior to an image in verification tasks may prime the participant and mask the surface color effects (Joseph and Proffitt, 1996). Throughout these research examples, items were presented in singular form and displayed against a neutral backdrop in a controlled environment. No such experiment compared images displayed in the global environment. Therefore, it cannot be assumed that a participant may be able to identify an apple in a tree faster when presented in color than in monochrome. Knowing that natural color may generally enhance object recognition, the same theories that are applied to pseudo-color that is displayed by fused sensor displays may be erroneous. Research into exploring the potential benefits of adding color to a scene is currently ongoing and also shows inconsistent results. The following is a brief synopsis of some research studies being conducted concerning color fusion.

Current sensor fusion research that examines the potential advantages of pseudo-color over monochrome is based on three types of experiments. These types are paired comparisons, reaction time and mean detection accuracy, and the accuracy of target

detection.

In the paired comparison type of experiment, participants are presented a random sequence of image pairs and are asked to respond to the "better" presentation. The goal of this type of experiment is to show differences in the preferred ordering of the sensors and to deduce if fusion based sensor imagery is more preferred than an individual sensor display. This type of experiment was utilized by Krebs, Buttrey, Lewis and McKenzie (1997) to identify a preferred sensor for use in a low-vision environment. In this experiment, participants were shown pair-wise comparisons of 25 different scenes using five different sensor formats. These formats were image intensified (I^2), infra-red, fused monochrome and two different fused color algorithms. The participant was tasked to choose a preferred format while locating a navigational cue contained within the scene. The results of the experiment were inconclusive. It was assumed that the inconsistencies that resulted from the experiment were due to a sensor to scene interaction. Sensors appeared to perform differently depending on the presented scene characteristics such as the texture, color and content. Although a slight advantage in recognizing objects using the color-fused techniques was shown, participant performance was actually very dependent on the type of navigational cues used. Results across all conditions were inconsistent (Krebs, Buttrey, Lewis and McKenzie, 1997).

Measurement of search accuracy and reaction times appear to provide a better foundation in the effort to determine if sensor fusion imagery is preferred over achromatic imagery. Steele and Perconti (1997) conducted a series of tests to determine if the use of color fusion imagery enhanced the performance or improved the situational awareness of helicopter pilots during low-visibility flights. The experiment was a part-

time simulation and identification task using 25 different scenes collected from the sensor combinations in both still frame and video format. The Advanced Helicopter Pilotage System (AHPS) was used to collect a series of night pilotage maneuvers using various sensor combinations. This imagery was then used to determine horizon perception, object recognition, identification and geometric perspective tasks. In the still-frame experiment, scenes were randomly presented for at most 10 seconds. Participant response time (YES/NO) and accuracy data was collected from specific information extracted from the scene. Object recognition and identification tasks required the participants to determine if a specific object was present or not. These tasks also required the participant to locate a specific object and determine its position in the field of view or to describe the object in detail. An observer was also required to determine if any object existed that would hinder the flight while the aircraft was on its intended flight path. Horizon perception tasks required participants to determine whether the horizon was level or not. The geometric perspective tasks required the participant to identify the shape or orientation of a feature using monocular perception cues (Steele and Perconti, 1997). The results of the still-frame experiments showed that fused imagery, whether color or monochrome, led to better performance, but the performance was highly dependent on the particular fusion algorithm, the particular visual task, and the scene content (Steele and Perconti, 1997).

The second experiment utilized short (17 to 31 second) video clips that were collected by the AHPS. These video clips were presented to participants in one of five different formats that tested response time and accuracy while identifying a specific object. Following each video sequence, participants were asked to rate the imagery based

on the five point Likert scale. The results failed to identify a preferred individual sensor format. The preference of a sensor format was scene specific (sensor to scene interaction) and that no particular sensor was found to be "desirable" for night helicopter pilotage. This experiment confirmed the previous experimental findings that sensor fusion is highly dependent on the algorithm used, as well as task and scene content (Steele and Perconti, 1997).

Toet, Ijspeert, Waxman and Aquilar (1997) conducted a study to investigate whether increasing scene detail with sensor fusion would improve a participants ability to perform a situational awareness search task. Images were collected using both visible and infra-red sensors that consisted of scenes taken at dawn when low light conditions and minimal thermal contrast existed. During the image collection process, a target was presented that contained a high infra-red contrast. The images were fused into four different formats consisting of color and monochrome. Participants were instructed to identify location and error distances. The data for the incorrect responses was then calculated. The results showed that participants performed better using fused color images when compared to fused monochrome and individual sensor images (Toet, et al., 1997).

These inconsistent sensor fusion studies may be attributed to the differences in fusion algorithms used in the various experiments and to the differences in the employed psychophysical tasks. A reason for the inconsistent results may result because fused imagery does not always improve participant performance when compared to individual sensor imagery. There may exist certain conditions when the fusion process aids performance and other situations when fusion is not necessary. If this were true, the

experiments should be designed that precisely elucidate when and where the fusion process is helpful. A more probable explanation and one that is easy to control is that proper experimental methodology for adequately testing these images has not yet been employed. These previous studies contain potential experimental methodological problems that may hinder accurate evaluation of the various image processes.

G. HYPOTHESIS

A significant deficiency in color fusion research is that researchers have attempted to utilize the findings from natural and achromatic studies and correlate the principles to the false-color theories that are used in sensor fusion. The majority of the color studies were conducted in the laboratory environment, utilizing single, defined natural or manmade objects observed in an unnatural setting. Comparing the findings from these types of experiments to research being conducted with natural scenes and a mixture of living and non-living objects is a significant threat to external validity. No known studies have been found that compare HVS perception of a global scene with the same scene observed with imagery obtained from a fused color sensor.

The experimental complexity of sensor fusion studies has proven to be overwhelming in the search for verification that it provides a better, more appealing scene for the observer. Efforts have generally focused on the end product of object recognition and have only shown that the performance of fusing combinations of night sensors varies with the algorithms used and scene condition. A significant deficiency to sensor fusion is that in some environmental conditions, observers have exhibited better performance with individual sensor imagery. The research conducted espouses the superiority of fused imagery by using specific environmental conditions or subjective operator opinion. In light of these inconsistencies, this thesis will attempt to relate individual preferences

between identical scenes manipulated with various color, pseudo-color and achromatic formats.

Natural scenes have been carefully selected by pre-designated standards taken from a commercially available collection of digital photographs on a Softkey Photo Gallery CD published by the Learning Company. Some of the categories of images were scenes from the states of Washington, Utah, and Colorado; farming scenes, and pictures of animals; and pictures of sporting events. Each sensor was identically manipulated so that the only difference a participant would see was the particular color or monochromatic format. Reducing the variability of processing with same scene displays controls the cognitive process. The feature maps associated with an image and the effects of sensor fusion can then be determined. The feature maps are dependent on the overall scene context. Sufficient scenes have been selected to ensure the experiments look across multiple real world scene environments and not just those that have shown superior fusion performance.

Two experiments were conducted to measure subject accuracy (error rates in percent) and reaction time (in milliseconds) by determining the orientation of natural color, artificial color, and achromatic scenes. The purpose of the experiment is to determine which type of scene is preferred between natural color, false color or monochrome, and to identify specific deficiencies that may cause false color scenes to be processed less efficiently.

The second experiment will be identical to the first experiment except Gaussian noise will be substituted for false saturation. This experiment will compare the findings of the previous experiment under ideal conditions with the findings under conditions of

low resolution. This may add validity to previous findings that color is useful to help segment object shapes in the absence of defined edge information. Additionally, this experiment will closely match true representations of imagery displayed to a user when using a fused device under realistic conditions.

In lieu of the previous studies, it is expected that reaction times and accuracy for false color scenes will be slower and less accurate when compared to a natural color or achromatic scene. Under degraded conditions, it is hypothesized that the effect will be more severe, that natural color imagery will be highly preferred compared to a false-color and achromatic scene. A level of significance of $\alpha = 0.5$ will be used for all statistical purposes.

THIS PAGE INTENTIONALLY LEFT BLANK

III. EXPERIMENT I

A. METHODS

1. Participants

Twenty students from various military services and job specialties undergoing academic studies at the Naval Postgraduate School or at the Defense Language Institute volunteered for this study. All participants, by self-report, possessed normal color vision and had at least 20/20 corrected vision. Participants were uninformed concerning the purpose of the experiment. Before participating in the experiment, participants were granted informed consent.

2. Apparatus

The experimental workstation consisted of a 200 MHZ Pentium personal computer equipped with a Texas Instrument TMS-340 Video Board and the corresponding TIGA Interface to Vision Research Graphics software. Stimuli were presented on an IDEK MF-8521 High Resolution color monitor (21" X 20" viewable area) equipped with an anti-reflect, non-glare, P-22 short persistence CRT. Pixel size was .26" horizontal and .28" vertical; the resolution was 800 X 600 square pixels and the frame rate was 98.7 Hz. The brightness of the monitor was linearized by means of an eight-bit color look-up table (LUT) for the red, blue and green guns. Responses were recorded on the number pad of a standard (IBM clone) keyboard. Moderate ambient luminance (1.2 cd/m^2 luminance) was maintained using a small floor lamp placed on the floor behind the IDEK monitor. Viewing distance was approximately 150 centimeters and the subjects were free to move their heads. A chair was provided for subject comfort and to help maintain the appropriate distance and viewing angle. Overhead lights were extinguished and subjects were required to adapt to the darkness for approximately two

minutes prior to conducting the experiment.

3. Stimuli

Each of 270 images (30 of which were designated for practice) was presented in one of eight different formats. These formats were natural color, color with false hue, saturation, or both hue and saturation manipulated, natural gray and gray with false hue, saturation, or both hue and saturation manipulated. Images were also presented in an upright or inverted position, so that each image was presented in 16 possible ways.

Construction of the experiment stimuli began by choosing images under specific pre-arranged criteria determined by two vision science experts. The criterion for selection was that a horizon was not present to contribute to identifying orientation. Images that contained reflections and shadows were eliminated because they may confuse the participant. All image manipulations were performed using Adobe Photoshop Version 4.0 Illustrator Software. The images were first cropped to a square 400 X 400 pixel size. Each of the 270 images was then manipulated within the Photoshop software using the standard image processing functions.

The hue of the images was manipulated by adjusting the hue value of each pixel and replacing it by its complementary color. The concept of complementary colors arises from a modern version of Newton's color wheel. The color wheel organizes all the colors according to the visible light spectrum wavelengths. The exception to the color wheel organization is the region that is complementary to the green region. This region is called the nonspectral hue. It is produced by various combinations of the other colors. The color magenta is a combination of the blue and red colors (Figure 10). The remainder of the colors on the color wheel represent only the monochromatic colors – those colors that are produced by a single wavelength (Matlin and Foley, 1997).

The complement of a color is found by drawing a straight line from a particular color, through the wheel center, to the intersection on the opposite side of the wheel. For example from Figure 10, the complementary color of yellow is blue. It was in this manner that the color of the images in the two experiments were changed.

There are two different ways in which color is mixed. Additive mixture of colors infers that particular light beams are combined, not the color pigments from the respective parts of the spectrum. Additive mixing of complementary colors, such as mixing blue and yellow in equal portions, produces gray. The subtractive mixture of colors infers that the color pigments are mixed, or that two or more colored filters are placed together and a light beam is emitted through these filters. The subtractive mixing of blue and yellow produces green (Matlin and Foley, 1997).

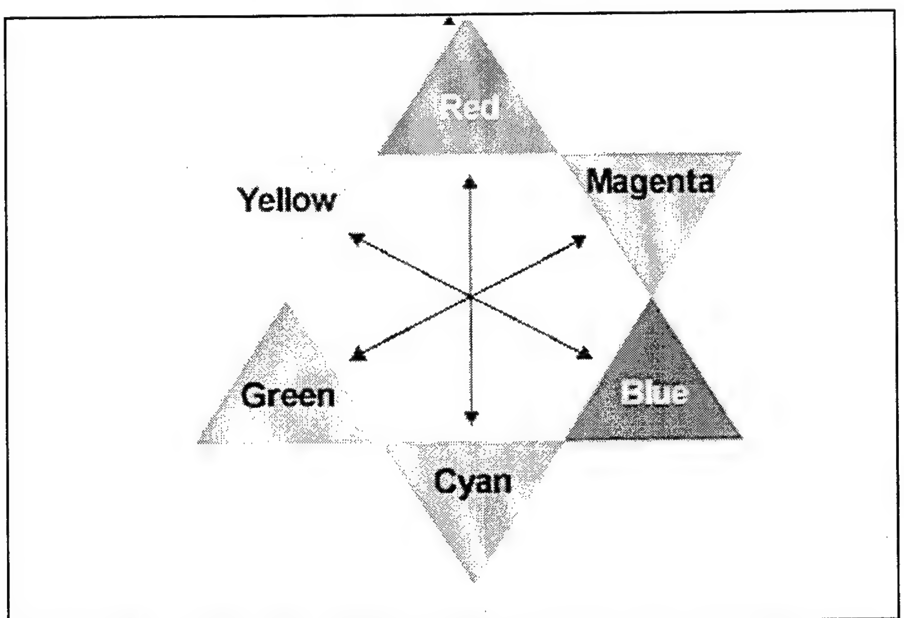


Figure 10: Illustration of the modern color wheel.
Courtesy of http://www.ricklineback.com/term4.htm

The Photoshop software provides a slide bar with a range from –180 degrees (counterclockwise from 0) to +180 degrees (clockwise from 0) for hue manipulation.

Rotating along the color wheel –180 or +180 degrees results in the exact same outcome; the original image's color complement. For consistency, all images were reassigned a value of +180 degrees. Figure 11 shows an original image and the image's color complement (image manipulate for hue). As seen, altering an image's hue gives it an unnatural appearance.

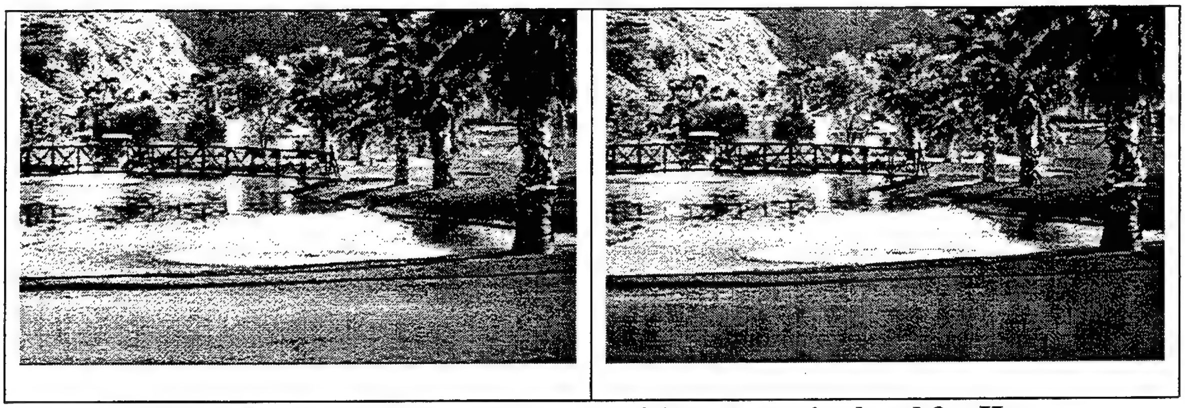


Figure 11: Natural colored image and image manipulated for Hue. Courtesy of Softkey Photo Gallery CD published by the Learning Company

The image's saturation was manipulated by taking each color pixel and fully saturating the color. Colors high in purity (saturation) are arranged around the edge of the color wheel. As the saturation level moves toward the center of the color wheel, the colors become increasingly less pure and more faded, moving toward an evenly balanced mixture of wavelengths with no single wavelength dominance (Sekular and Blake, 1994). Referring to the color wheel in Figure 12, saturation is seen as the apparent purity of a color.

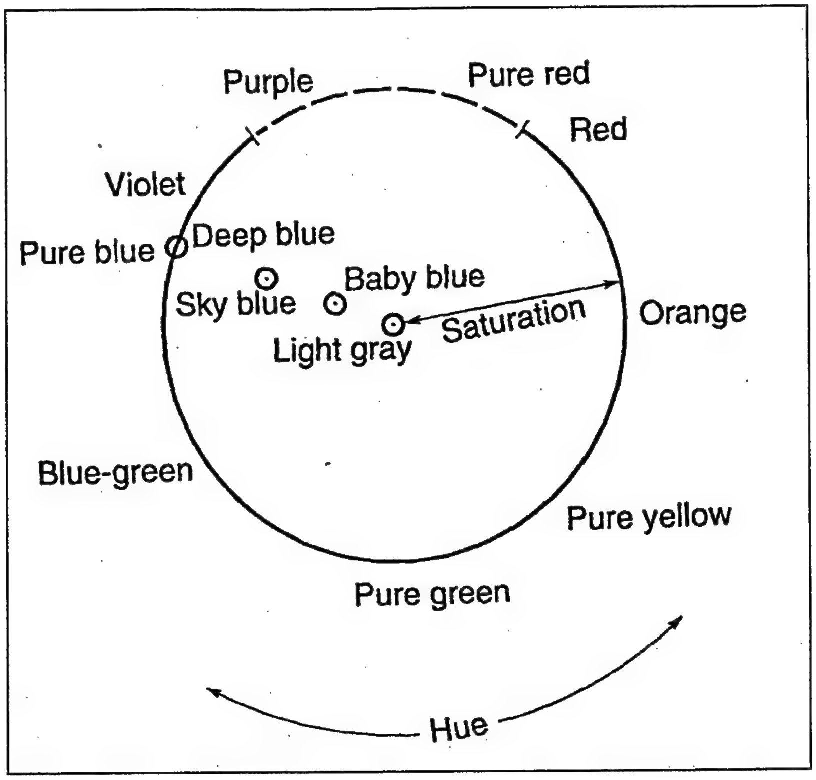


Figure 12: Color wheel plus Saturation. Notice how the color blue becomes lighter as it moves toward the center of the color wheel. (Matlin and Foley, 1997)

Photoshop software provides a slide bar with a range from –100 to +100. An image reassigned a value of +100 is considered to be totally saturated. An image reassigned a value of -100 is considered to be achromatic. All images were reassigned a value of +100. Figure 13 shows an original image and the image manipulated by changing its saturation. For example, a saturated blue, one lying on the color wheel edge, is perceived as deep hue; an unsaturated blue, close to the color wheel origin at the same hue, is perceived as a very light blue or baby blue. As seen, altering an image's saturation will not adversely change the color, it only changes the brightness of the image.

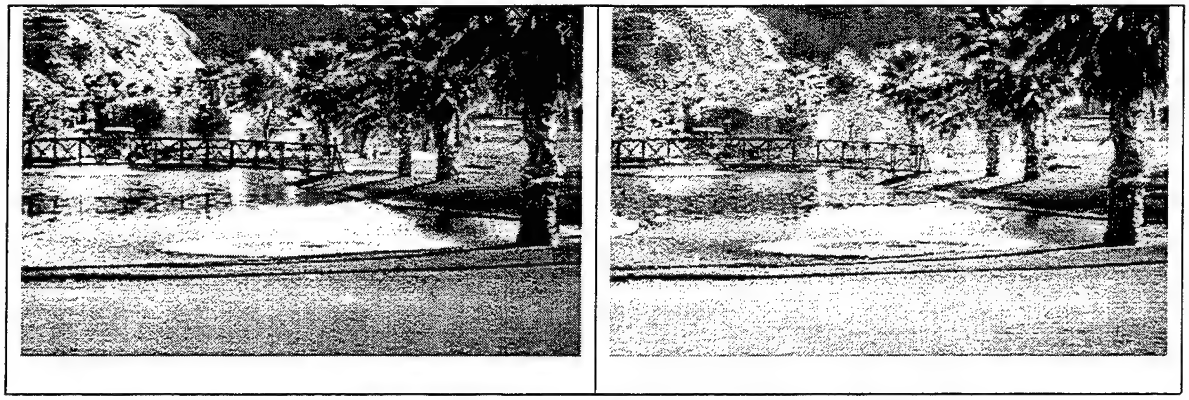


Figure 13: Natural colored image and image manipulated for Saturation. Courtesy of Softkey Photo Gallery CD published by the Learning Company

To manipulate an image for both hue and saturation, the values for the images were reassigned by the Photoshop software a hue value of +180 degrees and the saturation value of +100. Figure 14 provides a visual representation of the original image and the image with both the hue and saturation manipulated.

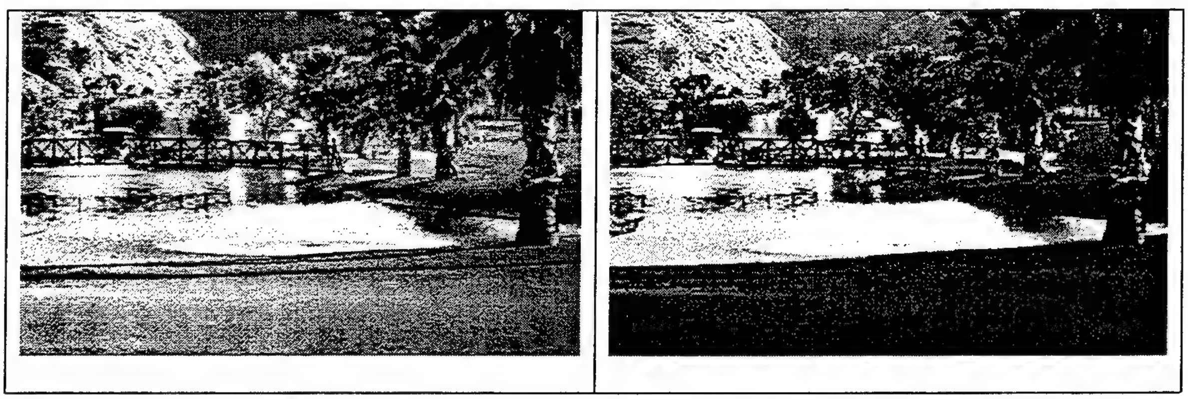


Figure 14: Natural colored image and image manipulated for Hue and Saturation. Courtesy of Softkey Photo Gallery CD published by the Learning Company

Achromatic images were first manipulated in the same fashion as the natural colored images, then converted to grayscale. The purpose of the grayscale images was to provide a control for changes in luminance that might accompany manipulations of color. Each image representation is seen in Figure 15.

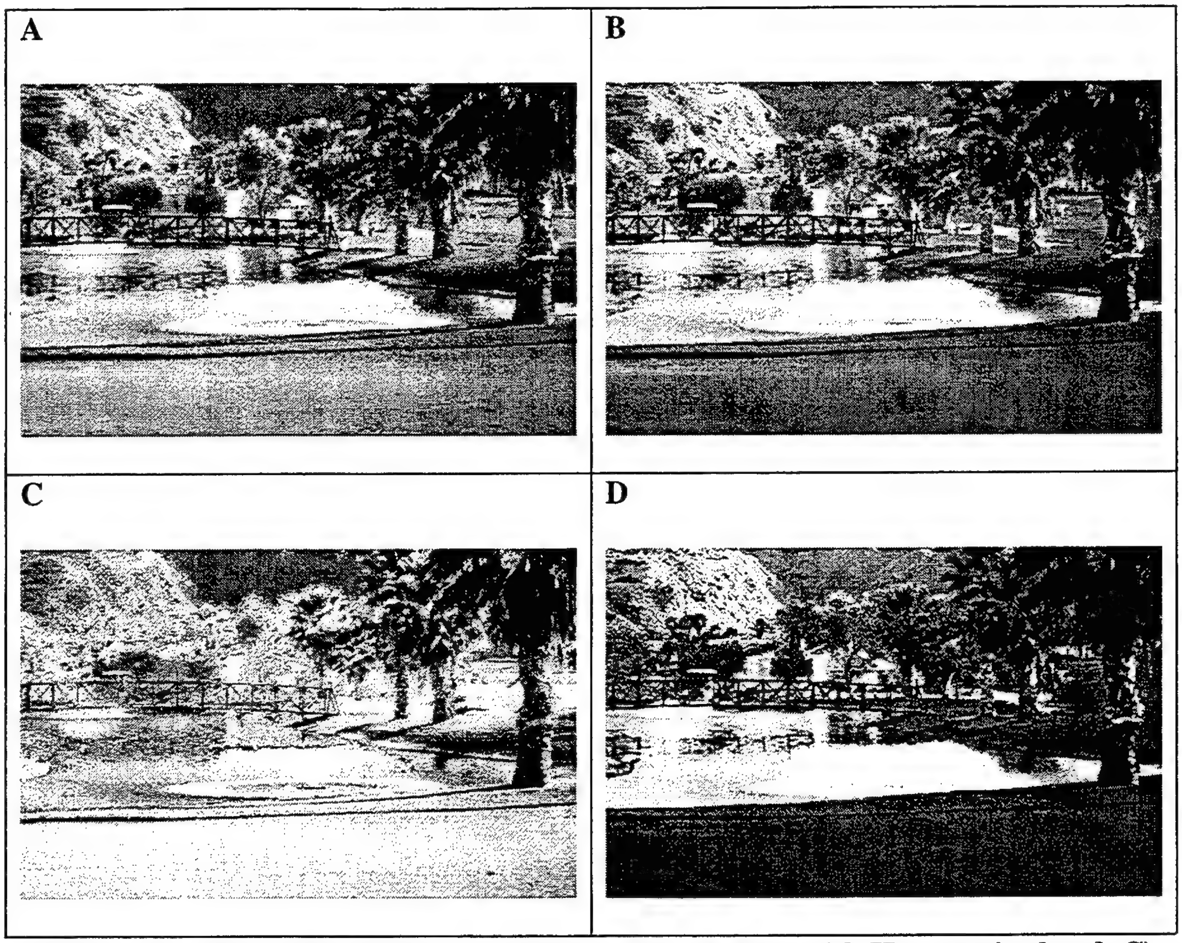


Figure 15: Achromatic images: A) natural gray, B) gray with Hue manipulated, C) gray with Saturation manipulated, D) gray with Hue and Saturation manipulated. Courtesy of Softkey Photo Gallery CD published by the Learning Company

4. Procedure

To prevent learning, each subject participated in one but not both experiments. Additionally, each image was viewed once in one of the various formats. Each subject was thoroughly briefed only on the background and procedures of the experiment and was given the opportunity to ask questions. Subjects were instructed to indicate as rapidly and accurately as possible with a keypress, whether the image orientation was upright (by pressing 1) or inverted (by pressing 2). Each image remained on the screen until the subject responded. A computer generated audio tone provided feedback following each incorrect response. Subsequent images were presented following a

response after a slight delay. After 30 consecutive image presentations, the experiment paused to allow the subject an opportunity to relax. The experiment restarted when the subject pressed any key. The entire experiment lasted approximately 20 minutes.

Each subject was given a block of thirty practice trials prior to the experiment. The practice trials were presented in the same format as the experiment. Upon completion, subjects were offered a brief pause to ask any questions. The actual experiment then commenced and the participants were presented with 240 images. Reaction times and accuracy were collected for each trial.

5. Experimental Design

The design was a 2 X 2 X 2 X 2 within-subjects factorial design. Factors included orientation (upright or inverted), color (color or gray), hue (natural or false) and saturation (natural or false). Each of the 16 cells contained 15 observations for a total of 240 data points. Reaction times for incorrect responses and responses to the 30 practice images were not included in the data analysis. There were no theoretical expectations of the colors effect on inverted images from prior research, therefore, the reaction times to inverted images were also discarded. However, inverted error rates were recorded and viewed to ensure participants did not display any bias toward a particular orientation selection.

B. DEVELOPMENT OF THE VISUAL MODEL

As with any psychophysical experiment, inconsistencies occur between each subject's response times and error rates. These differences arise in part due to variances in individual participants, image conditions and manipulation. To account for these differences, the following model is proposed:

$$\text{Reaction Time}_{ijklmn} = \text{Part}_i + \text{Color}_j + \text{Hue}_k + \text{Sat}_l + \text{Image}_m + \text{error}_n$$

where Part_i represents the ith participant of the experiment;

Color_j represents the color of the image (natural or monochrome);

Hue_k represents the hue condition of the image (natural or false);

Sat_l t represents the saturation condition of the image (natural or false);

Image_m represents each presented image and

Error_n represents for unaccounted variations within the model.

C. RESULTS

To determine the appropriate statistical method for the results of the experiment, normality tests were conducted and showed that the data failed to follow the properties of normality. Therefore, the assumption that the original data was normal was not tenable. As seen below, the analysis will proceed on intra-subject differences in reaction times and error rates and while these might not be exactly normal, the t-test is well-known to be robust against minor deviations from normality.

Mean reaction times (in milliseconds) and mean error rates (in percent) for each of the participants (Appendix C) were calculated from individual performances for each condition. To ensure participants did not show any bias toward any particular keypress, the mean error rates were observed for the upright and inverted conditions. If the error rates for the upright representations were zero percent, it would indicate that the participant displayed a bias towards the "1" keypress. If this were the case, the mean error rates for the inverted orientations would be very large. For this experiment, no bias toward a particular keypress was noted. Additionally, comparing the mean reaction time and error rates for each condition may show the existence of a speed/accuracy trade-off.

A low error rate and unusually large reaction time indicates that a participant is very careful in selecting the proper orientation. Conversely, a high error rate and small reaction time indicates that a participant is hasty in making decisions. The experimental data correlates with respective categorical speed/accuracy trade-off relationships in that higher reaction times were generally accompanied by higher error rates. When images were manipulated from their natural color or gray conditions, participant reaction time and error rates increased. Box plots and line plots of each condition are seen in Figures 16 and 17. The box plot was chosen because it gives readers quick visual information about the data spread within a variable and offers a comparison between variables. The box plot consists of a few basic elements: the upper (shaded area) quartile, the lower (shaded area) quartile and the median (the white line in the middle). The whiskers show the interval of values outside the box, or values that are no more than one and a half times the interquartile range. The interquartile range is defined as the difference between the upper and lower quartile. The horizontal lines far outside the boxplot represent outliers (Hamilton, 1992). The tabulated data can be seen in Table 1.

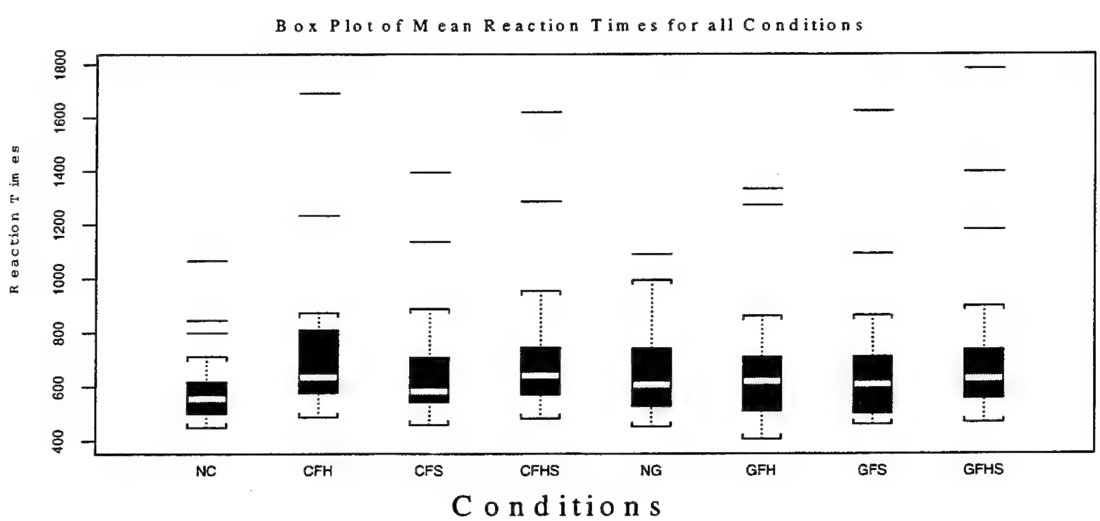
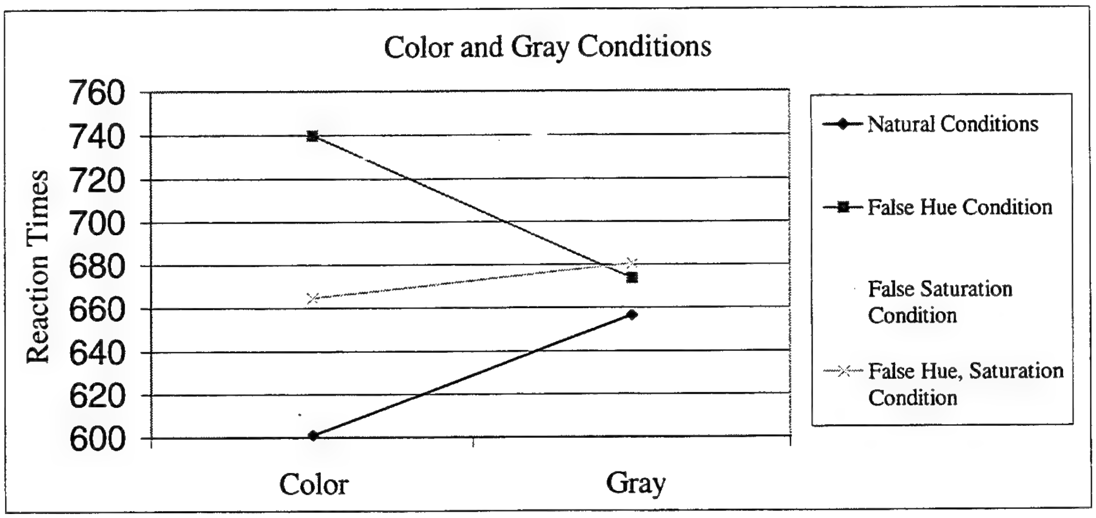


Figure 16: Box Plot of all image condition mean reaction times

By inspection of the box plot (Figure 16), the data for the natural color condition shows a lower median reaction time and smaller variance than the other image conditions. Outliers are shown to exist for each condition. These outliers are attributed to two specific participant's performance, implying that these participants were consistently slow across each condition in relation to other participants.



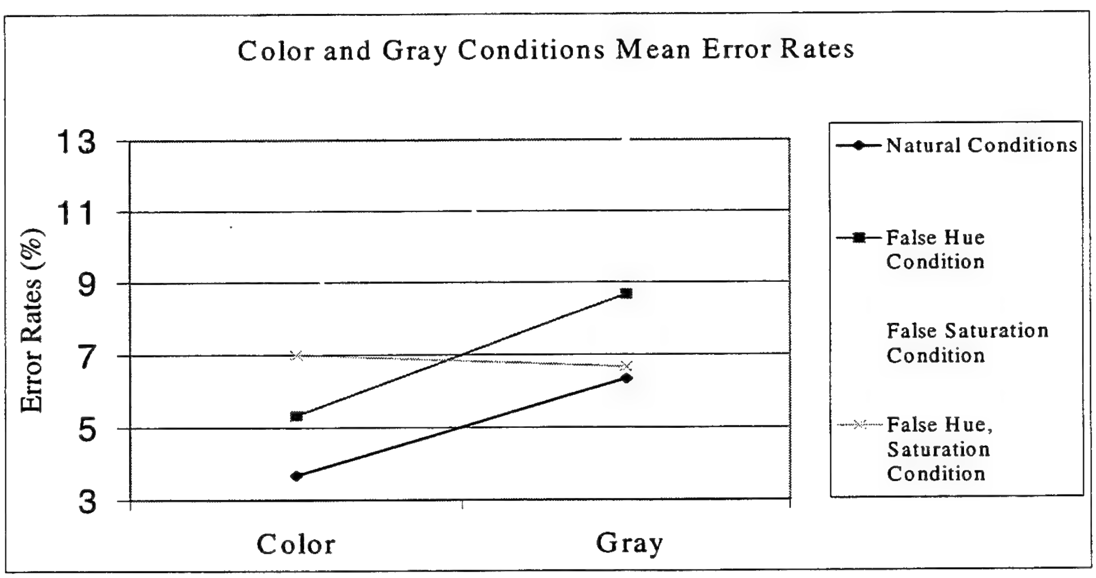


Figure 17: Line Plots of mean reaction times and error rates for Color and Gray conditions.

The line plot (Figure 17) offers a pictorial representation of Table 1. Generally, the mean error rates and reaction times are less for color conditions than for achromatic conditions. The reaction times for the color false hue and gray false hue conditions do not follow this trend, thereby displaying a possible effect for the color false hue condition. Also, the error rates between the color false hue and saturation and gray false hue and saturation condition appear to be fairly consistent between conditions, implying that a speed/accuracy trade-off does not account for these results. The remaining error rates and corresponding reaction time increased for images that were viewed in achromatic formats.

Table 1 shows that the average reaction times for the natural color and natural gray condition are smaller than the other image conditions. Smaller reaction times for these conditions were expected by the developed hypothesis because true scene representation is easier to detect than scenes that do not symbolize the true representation of the scene. Additionally, the error rate for natural color imagery was smaller, indicating that participants who view images under natural color conditions will not only respond faster but will be more accurate in object recognition. Images that were manipulated for hue and saturation produce longer reaction times and error rates, thereby supporting the hypothesis that manipulating the color of an image will disrupt the participant's ability to efficiently process image features.

	COLOR				GRAY			
DIFF	**NC**	**CFH**	**CFS**	**CFHS**	**NG**	**GFH**	**GFS**	**GFHS**
Mean RT	601.05	740.03	664.76	726.20	656.52	673.75	680.50	745.52
SEM	34.05	63.13	51.77	62.55	38.13	53.86	60.20	74.94
Mean Err	3.67	5.33	7.00	8.67	6.33	8.67	6.67	13.00
SEM	1.02	1.33	1.78	1.61	1.64	1.82	1.53	2.49

Table 1: Tabulated data for each conditions mean reaction time and error rate.

where RT represents the reaction time of the participant selecting an orientation;

SEM represents the standard error of the means;

NC represents the natural color condition;

CFH represents the color false hue condition;

CFS represents the color false saturation condition;

CFHS represents the color false hue and saturation condition;

NG represents the natural gray condition;

GFH represents the gray false hue condition;

GFS represents the gray false saturation condition and

GFSH represents the gray false hue and saturation condition.

Because we hypothesize that there is a difference in reaction time between natural and artificial color scenes, the difference between each condition's mean and natural color's mean should be positive. Table 2 shows the difference of the means between each condition.

		Color			Gray	
DIFF	**CFH-NC**	**CFS-NC**	**CHFS-NC**	**GFH-NG**	**GFS-NG**	**GFHS-NG**
Mean RT	138.98	63.71	125.14	17.24	23.99	89.00
SEM	34.80	34.80	35.60	38.40	47.59	53.08
Mean Err	1.67	3.33	5.00	2.33	0.33	6.67
SEM	1.59	1.49	1.67	2.07	2.08	2.37

Table 2: Difference of the reaction time and error rate means across all conditions. Notice all values are positive indicating that reaction time and error rates for natural color scenes are smaller.

The difference of the means of each condition in Table 2 is not the same; therefore, we may conclude by inspection that there can be an effect on reaction times for each condition. These positive values indicate that the participant, when observing natural conditions will exhibit better performance. The comparison results displayed in

Table 2 strengthen the assumption that individual perception is negatively disrupted when altering an images natural condition. To test the data, a paired t-test using Bonferroni's inequalities with an $\alpha = 0.05$, six samples and a confidence level of 99.2% was used. When comparing the color false hue condition versus the natural color condition reaction time ($\underline{t}(19) = 3.9935$ $\underline{p} \leq .008$) and accuracy ($\underline{t}(19) = 1.045$ $\underline{p} \geq .008$), an effect for reaction time was found. This indicates that a participant's perception is disrupted when changing the image's hue. Comparing the color false hue and saturation versus the natural color condition reaction time ($\underline{t}(19) = 3.5148$ $\underline{p} \leq .008$) and accuracy ($\underline{t}(19) = 3.0009$ $\underline{p} \leq .008$), an effect was also found. Not only were the participant reaction times significant, but the error rates were also significant. The fact that the combined hue and saturation condition was significant may mean that an interaction between the conditions might exist. A test for the presence of interaction will be conducted later. The remaining comparisons from Table 2, color false saturation versus natural color condition reaction time ($\underline{t}(19) = 1.8308$ $\underline{p} \geq .008$) and accuracy ($\underline{t}(19) = 2.2361$ $\underline{p} \geq .008$), gray false hue versus natural gray condition reaction times ($\underline{t}(19) = t = 0.4489$ $\underline{p} \geq .008$) and accuracy ($\underline{t}(19) = 1.1278$ $\underline{p} \geq .008$), gray false saturation versus natural gray condition reaction time ($\underline{t}(19) = 0.5041$ $\underline{p} \geq .008$) and accuracy ($\underline{t}(19) = 0.1599$ $\underline{p} \geq .008$), and gray false hue and saturation versus natural gray condition reaction time ($\underline{t}(19) = 1.6768$ $\underline{p} \geq .008$) and accuracy ($\underline{t}(19) = 2.8133$ $\underline{p} \geq .008$) revealed no effect. The absence of an effect for color false hue versus natural gray provides evidence that manipulating an image by altering the saturation may not effect a participant's reaction time. This also applies to images viewed under monochrome conditions where manipulation for saturation did not affect a participant's perception. These results may add evidence that when altering an

image by hue and saturation, the hue effect may influence the combined hue and saturation effect on participant reaction time. Since achromatic images contain neither hue nor saturation levels, the statistical t-tests agree with the inference that there is no significant difference between the natural gray and false gray conditions.

Luminance tests were also conducted by comparing the false gray conditions to the natural gray images. For luminance to be a factor, the difference of the means between false gray and natural gray conditions shall be a value other than zero. Table 2 shows that these differences are positive and the values are much less than the values of the color conditions. However, as noted above, respective statistical t-tests showed no effect across each false gray condition when compared to the natural gray condition. Therefore, the effects of the color conditions were due to color and not to a luminance confound.

To determine if altering an image's hue had any effect on participant reaction time and error rates, the hue effect was removed from the images by subtracting all conditions of natural hue from the corresponding conditions of false hue. For example, the difference in the mean reaction time and error rates for the conditions of color false saturation and both color false hue and saturation removes the saturation effect and leaves only the effect of hue on the image. Under the hypothesis, there will be a difference in the reaction times of these conditions. Table 3 displays the results.

DIFF	HUE CFH-NC	CFHS-CFS	GFH-NG	GFHS-FGS
Mean RT	138.98	61.43	17.24	65.01
SEM	34.80	43.23	38.40	42.03
Mean Err	1.67	5.00	2.33	6.67
SEM	1.59	1.67	2.07	2.37

Table 3: Difference in reaction time and error rate means across all image conditions with and without Hue.

To test the data, a paired t-test using Bonferroni's inequalities with an $\alpha = 0.05$, four samples and a confidence level of 98.75% was used. In tests of the color false hue condition versus the natural color condition reaction time ($t(19) = 3.9935$ $p \leq .0125$) and accuracy ($t(19) = 1.045$, $p \geq .0125$), a reaction time effect was found. This effect has already been explained above. The remaining comparisons from Table 3, color false hue and saturation versus color false saturation condition reaction time ($t(19) = 1.4212$ $p \geq .0125$) and accuracy ($t(19) = 0.7373$ $p \geq .0125$), gray false hue versus natural gray condition reaction time ($t(19) = 0.4489$ $p \geq .0125$) and accuracy ($t(19) = 1.1278$ $p \geq .0125$), and gray false hue and saturation versus gray false saturation condition reaction time ($t(19) = 1.5467$ $p \geq .0125$) and accuracy ($t(19) = 2.2637 p \geq .0125$) showed no effect.

To determine if altering an image's saturation had an effect on participant reaction time and error rates, the saturation effect was removed from the images by subtracting all conditions of natural saturation from the corresponding conditions of false saturation. For example, the difference in the mean reaction time and error rates for the conditions of color false hue and both color false hue and saturation removes the hue effect and leaves only the effect of saturation on the image. Under the hypothesis, there will be a difference in the reaction times of these conditions. Table 4 displays the results.

	SATURATION			
DIFF	**CFS-NC**	**CFHS-CFH**	**GFS-NG**	**GFHS-FGH**
Mean RT	63.71	-13.83	23.99	71.76
SEM	34.80	24.93	47.59	32.25
Mean Err	3.33	3.33	0.33	4.33
SEM	1.49	1.64	2.08	2.12

Table 4: Difference in reaction time and error rate means across all image conditions with and without Saturation.

To test the data, a paired t-test using Bonferroni's inequalities with an $\alpha = 0.05$, four samples and a confidence level of 98.75% was used. In tests of the color false saturation condition versus the natural color condition reaction time ($t(19) = 1.8308$ $p \geq .0125$) and accuracy ($t(19) = 2.2361$ $p \geq .0125$), color false hue and saturation versus color false hue condition reaction time ($t(19) = -.5549$ $p \geq .0125$) and accuracy ($t(19) = 2.0329$ $p \geq .0125$), gray false saturation versus natural gray condition reaction time ($t(19) = .5041$ $p \geq .0125$) and accuracy ($t(19) = 0.1599$ $p \geq .0125$), and gray false hue and saturation versus gray false hue condition ($t(19) = 2.2254$ $p \geq .0125$) and accuracy ($t(19) = 2.0409$ $p \geq .0125$), failed to produce evidence that altering an image's saturation effects participant reaction and error rates. Each condition indicates that whether viewing a natural color image or achromatic image, an effect on participant reaction time and error rates when viewing an image that has been altered for saturation does not exist. This is because changing the image saturation does not drastically change the image color, it only brightens the entire color spectrum of the image. It is interesting to note that participant reaction time when viewing a false color image that had been manipulated for hue and saturation was less than the reaction time when viewing a color image that had been manipulated for hue. This may suggest that the brightness of the image due to the altered saturation level may enhance participant performance when compared to a color image that was manipulated for hue.

To determine the effects of color, we compare the differences between the mean reaction time and error rates of each color condition with the means of the same images in the achromatic condition. For example, the difference in the reaction time and error rate means between natural gray and the natural color condition will be negligible. For a condition of color to be a factor, there will be a difference in the means across each condition. Table 5 displays the results.

	GRAY-COLOR			
	NG-NC	**GFH-CFH**	**GFS-CFS**	**GFHS-CFHS**
Mean RT	55.47	-66.28	15.74	19.32
SEM	31.65	23.74	45.44	37.99
Mean Err	2.67	3.33	-0.33	4.33
SEM	1.63	1.71	2.13	2.38

Table 5: Difference in reaction time and error rate means across all image conditions between Color and Monochrome.

To test the data, a paired t-test using Bonferroni's inequalities with an $\alpha = 0.05$, four samples and a confidence level of 98.75% was used. When comparing gray false hue versus color false hue condition reaction time ($t(19) = -2.7912$ $p \leq .0125$) and accuracy ($t(19) = 1.633$ $p \geq .0125$), a reaction time effect is found. As seen in Table 5, the reaction time for the gray false hue image is much smaller than the reaction time for the color false hue image. This indicates that participants are more apt to perceive an achromatic image faster than a color image that is altered for hue. This provides more evidence that the effect of hue is significant for a colored image. The other conditions, natural gray versus natural color condition reaction time ($t(19) = 1.7524$ $p \geq .0125$) and accuracy ($t(19) = 1.949$ $p \geq .0125$), gray false saturation versus color false saturation condition reaction time ($t(19) = .3465$ $p \geq .0125$) and accuracy ($t(19) = -0.1563$ $p \geq .0125$), and gray false hue, saturation versus color false hue, saturation condition reaction time ($t(19) = .5086$ $p \geq .0125$) and accuracy ($t(19) = 1.8183$ $p \geq .0125$), show no effect.

To employ a second method to validate the visual model, a statistically reliable one-sided t-test was conducted on the combination of similar image conditions using an $\alpha = 0.5$. By grouping individual conditions of a particular group (Figure 18) and comparing these conditions reaction time and error rate means that do not possess the groups stated manipulation, the following result is shown in Table 6.

COMPARING HUES

Color False Hue	Natural Color
Color False Hue and Saturation	Color False Saturation
Gray False Hue	Natural Gray
Gray False Hue and Saturation	Gray False Saturation

Figure 18: Stacked comparison of all viewing conditions with and without Hue manipulated

Difference between Natural Hue and false Hue conditions	
Mean RT	72.54
SEM	18.69
Mean Err	3.00
SEM	1.11

Table 6: Reaction time and error rate means for images manipulated for Hue

Based on the data provided in Table 6, there is evidence that a reaction time ($t(79) = 3.8807$ $p \leq .05$) and accuracy ($t(79) = 2.6982$ $p \geq .05$) effect exists. This reaction time effect is also present in the previous tests that compare hue and images that are not manipulated for hue. These results provide evidence that manipulating an image's hue will disrupt participant visual perception.

To determine if a saturation effect exists, reaction time and error rate means of the

images that contain natural saturation were compared to the reaction time and error rate means of the images that contained false saturation. Figure 19 shows these conditions.

COMPARING SATURATION

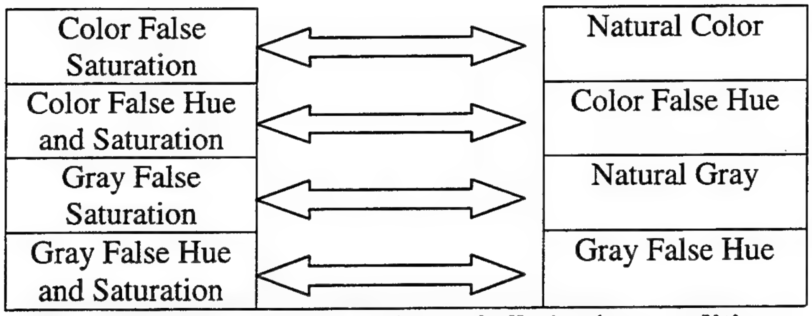


Figure 19: Stacked comparison of all viewing conditions with and without Saturation manipulated

Difference between Natural Saturation and false non-Saturation conditions	
Mean RT	36.41
SEM	17.99
Mean Err	2.83
SEM	0.92

Table 7: Reaction time and error rate means for images manipulated for Saturation

The difference of the mean reaction times between saturation conditions reaction time ($t(79) = 2.0236$ $p \leq .05$) and accuracy ($t(79) = 3.0643$ $p \leq .05$) shows an effect. This result contradicts earlier results that test the effect of saturation on participant visual perception. The reason for this contradiction may be due to the large standard error for the mean reaction time and the increased degrees of freedom that occur by combining image conditions. However, it must be noted that the p-value ($p = 0.0464$) suggests that the effect of saturation is not very strong. There may also be some interaction between hue and saturation that may enhance the effect of saturation. A statistical test for interaction will be performed later.

Lastly, a comparison of color to monochrome conditions was conducted to determine if a color effect exists. Although altering images by changing color (hue and saturation) was included with natural color conditions, this comparison will determine whether color is more preferred than achromatic conditions. Figure 20 shows these conditions.

COMPARING COLOR TO GRAY

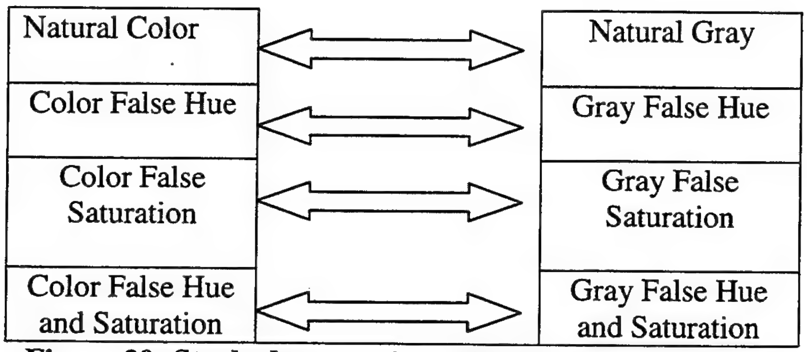


Figure 20: Stacked comparison of all viewing conditions with and without Color

Difference between Color and achromatic conditions	
Mean RT	-6.06
SEM	18.17
Mean Err	2.50
SEM	0.99

Table 8: Reaction time and error rate means for images with and without Color

Observing the Table 8 data for comparing color conditions with achromatic conditions reaction time ($\underline{t}(79) = -.3337$ $\underline{p} \geq .05$) and accuracy ($\underline{t}(79) = 2.5131$ $\underline{p} \leq .05$) an effect was found. The negative value for the mean reaction times indicates that participant reaction times are slightly smaller when viewing images in achromatic format when compared to a color format.

Strong evidence has already been shown that supports the fact that altering an

image's hue has a pronounced effect on participant's perceptual abilities. However, previous results indicate that an interaction may exist between hue and saturation when images are altered by these combined conditions. Using the hypothesis that there exists interaction between conditions of hue and saturation, the following linear model is developed:

$$\text{Reaction Time}_{ijklmn} = \text{Part}_i + \text{Color}_j + (\text{Hue}_k * \text{Sat}_l) + \text{Image}_m + \text{error}_n$$

where Part_i represents the ith participant of the experiment;

Color_j represents the color of the image (natural or monochrome);

$(\text{Hue}_k * \text{Sat}_l)$ represents the interaction between the two variables;

Image_m represents each presented image and

Error_n represents for unaccounted variations within the model.

By combining the effects of hue and saturation and running the linear model to test for interaction between the variables, no interaction is shown to exist ($\underline{t}(136) = -0.3968$ $\underline{p} \geq .05$). The individual values for hue ($\underline{t}(136) = -2.3837$ $\underline{p} \leq .05$) and saturation ($\underline{t}(136) = -1.0921$ $\underline{p} \geq .05$) also confirm the effect that altering hue will disrupt participant reaction time and error rates. This interaction model is strongly supported by a high coefficient of determination (R^2) of 81 percent, which shows the amount of the total variance explained by the model. Therefore, it is concluded that the effects for hue have a significant effect on participant reaction time. When an image is manipulated for both hue and saturation, they act independently of each other and it is the effect of hue that causes the increase in participant reaction time and error rates to increase.

D. DISCUSSION

The purpose of this experiment is to clarify the role of color in object recognition. Previous research has been inconclusive in adequately defining colors role. However, equipped with a large abundance of professionally photographed images, this experiment makes it possible to manipulate the images in eight different conditions for comparison. It was hypothesized that natural color scenes would be interpreted in a similar manner to scenes displayed achromatically. However, an artificial color scene altered for hue, saturation, or both hue and saturation, would degrade a participant's visual perception process when compared to either natural color or natural gray.

The methodology for this experiment originates by attempting to clarify colors role in the "real-world." Previous research defined colors role in controlled laboratory environments without using natural scenes, and defined color as a combination of natural color and artificial color. Natural objects were defined as living, and unnatural objects defined as non-living. Object recognition failed to emphasize the role of color in global scenes.

This experiment varied the chromatic format of the entire scene. Not only were individual objects altered in color, but the background and foregrounds were altered as well. Images were defined as natural if they were unaltered and artificial if they were altered in hue, saturation, or both. To provide a control measure, achromatic representations were developed for each color format. Additionally, luminance effects were determined by the comparison of natural gray to the other manipulated gray conditions. The experimental design employed a forced choice task, where observers were to indicate scene orientation.

Perhaps the preferred method in discussing the results of Experiment 1 is to

analyze the data from the combined or stacked image comparisons, then to analyze the data from individual image comparisons. This type of discussion will first show that generalizing color as both natural and artificial will display results that are different when color is analyzed in the respective individual natural and artificial format.

The results of analyzing the combined comparisons between color and achromatic scenes produced an effect for the error rate means. Although the reaction times means were slightly less for achromatic images, participants error more frequently which significantly affected their performance. This result suggests that color is beneficial in object recognition and validates the majority of previous research.

It is wrong to suggest that these findings be applied to studies in which artificial color is tested. The fact that previous research suggests that the HVS is disrupted when viewing non-prototypical objects, applying generalized color findings to experiments that alter color, is misleading. The HVS develops color mappings that may be recalled when necessary. When a conflict occurs between the recognition of a particular object and its stored color mapping features, a disruption occurs in the participant's ability to efficiently recognize the objects. The results of the comparisons for images that are altered for hue and those that are not manipulated for hue are significant. This finding suggests that once a natural scene is altered by changing the color, the HVS is disrupted. Analysis of the images that were altered for saturation was also significant. This result is surprising because when the saturation of the natural scene is modified, the brightness and not necessarily the color, is changed. However, it is shown that when an image is altered for hue and saturation, the effect for hue overwhelms and effect for saturation and causes the combined hue and saturation conditions to be significant, implying that either or both the

hue and saturation are disruptive. The results of the statistical tests for saturation are not strong and therefore, cannot suggest that image manipulation for saturation significantly disrupts the HVS. More studies should be conducted to validate this finding.

Another statistical method tested the comparisons of each image format against combinations of the other formats to find an effect for hue, saturation, and color. Each manipulated condition was compared to the natural format, whether it was color or monochrome. The differences in the mean reaction times and error rates showed a significant effect for color false hue and color false hue and saturation. The non-significant results of the achromatic comparison shows that luminance has no effect on participant perceptual ability. Because the effect for both hue and saturation is significant, the possibility of interaction between hue and saturation must be considered. A linear model was developed and results failed to show any hue and saturation interaction. Therefore, more evidence exists that suggests altering an image for hue disrupts the participant's ability to recognize objects. Image manipulation for saturation was then tested. The statistical results show a lack of evidence to suggest any effect on participant performance. Image manipulation for hue was then tested. Effects for hue were already found in the combined or stacked tests as well as the comparisons to the natural formats. The results of hue manipulation shows that an image altered for hue has an effect when compared to images in the natural format. Again, this suggests that altering the natural color of a scene adversely effects the participants ability to process the scene with the same efficiency as in natural color. Lastly, the specific color format manipulations were compared to the achromatic conditions. The results showed that changing the hue affects the HVS when it is compared to the same scene in achromatic

format. One interesting comparison to note is that no effect is found between a natural color scene and an achromatic scene. Although only 15 images were compared in these formats, this result adds validity to the hypothesis that natural color does not enhance object recognition when compared to a natural monochrome scene.

The results of Experiment 1 showed that depending on the specific experimental design employed, different results will occur. Grouping images by color and comparing them to images in achromatic format, performance with color imagery was found to be better. This result validates numerous color theories concerning object recognition. However, when separating the colors into natural and artificial categories, evidence shows that color may not be beneficial. As stated, the type of experimental design employed reveals different results. Due to the overwhelming evidence that implies that altering an images natural color will adversely affect participant performance in object recognition, the image format that is most preferred is the natural format. If scenes cannot be represented in the natural color, then the best alternative is to display the scene achromatically.

IV. EXPERIMENT 2

A. METHODS

1. Participants

As in Experiment 1, fifteen students voluntarily participated in this study. The participants did not take part in the previous experiment.

2. Apparatus

The same experimental workstation used in the previous experiment was used in Experiment 2.

3. Stimuli

Each of 270 images (30 of which were designated for practice) was presented in one of eight different formats. These formats were natural color and gray, and color and false gray with hue. Additionally, half of the images in each cell were presented with Gaussian noise added. Images were also presented in an upright or inverted position, so that each image was presented in 16 possible ways.

The experiment was constructed by examining the previous experiment stimuli and choosing the images that contained salient color contrast as judged by the author and one other vision science expert. Objects within the images that encompassed approximately 25% or more of the total viewing area were eliminated. These two selection processes eliminated approximately half the previous experiment images. Replacement images were selected from the same categories of images off the Softkey Photo Gallery CD. The images were cropped to a rectangular 250 X 400 pixel size, then manipulated using the Photoshop software's standard image processing functions. Image manipulations to generate the color false hue, natural gray and gray false hue conditions

were identical to those used in Experiment 1. Noise was added by increasing or decreasing the assigned value of each pixel by an amount chosen randomly from a Gaussian distribution with mean zero and standard deviation of 50. Pixel values of more than 255 or less than zero were set to values of 255 or zero respectively.

Procedures to convert the images to achromatic format were identical to those of the previous experiment. Figure 21 depicts each image representation.

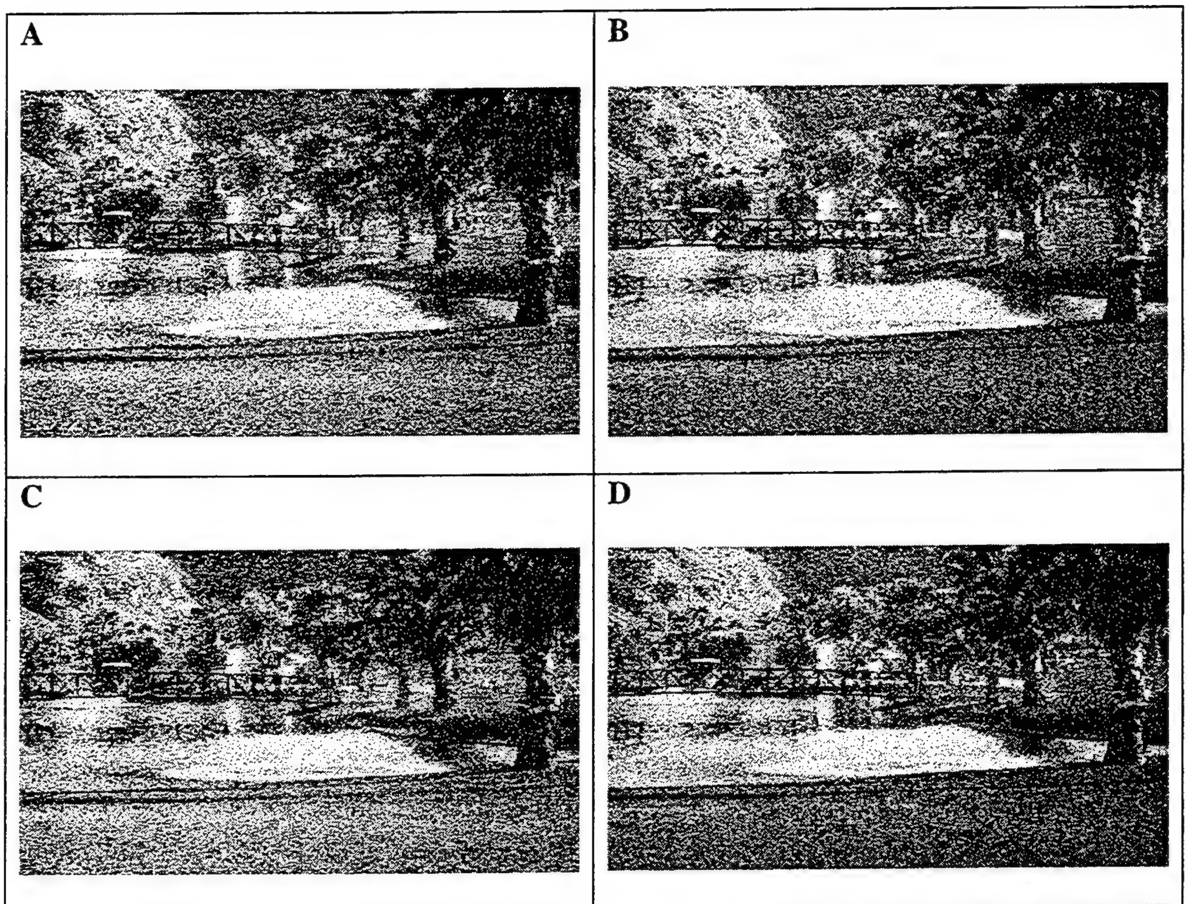


Figure 21: Image comparison with and without noise. A) Natural Color with Noise, B) Color False Hue with Noise, C) Natural Gray with Noise, D) Gray False Hue with Noise

4. Procedure

The same procedure used for the previous experiment was used in Experiment 2.

5. Experimental Design

The design for Experiment 2 was a 2 X 2 X 2 X 2 within-subjects factorial design. Factors included orientation (upright or inverted), color (color or gray), hue (natural or false) and noise (noise or no noise). The observations, number of cells, and data collection methods were identical to Experimental 1.

B. DEVELOPMENT OF VISUAL MODEL

Inconsistencies will also occur between each subject's response time and error rates similar to the data from the previous experiment. To account for the differences, the following model is proposed:

$$\text{Reaction Time}_{ijklmn} = \text{Part}_i + \text{Color}_j + \text{Hue}_k + \text{Noise}_l + \text{Image}_m + \text{error}_n$$

where Part_i represents the ith participant of the experiment;

Color_j represents the color of the image (natural or monochrome);

Hue_k represents the hue condition of the image (natural or false);

Noise_l represents the noise condition of the image (noise or no noise);

Image_m represents each presented image and

Error_n represents for unaccounted variations within the model.

C. RESULTS

To remain consistent with statistical testing employed in Experiment 1, the t-test with level of significance of $\alpha = .05$ was used. The reaction times (in milliseconds) and error rates (in percent) for each of the participants (Appendix D) were calculated to obtain the reaction time and error rate means for each condition of the experiment. As in Experiment 1, reaction time and error rate means were compared to determine participant speed/accuracy trade-off effects. Additionally, since error rates were not constant for

each inverted condition, bias effects were determined to be non-existent. A box plot and line plot of each condition is shown in Figures 22 and 23 to provide the reader a rapid view of the data.

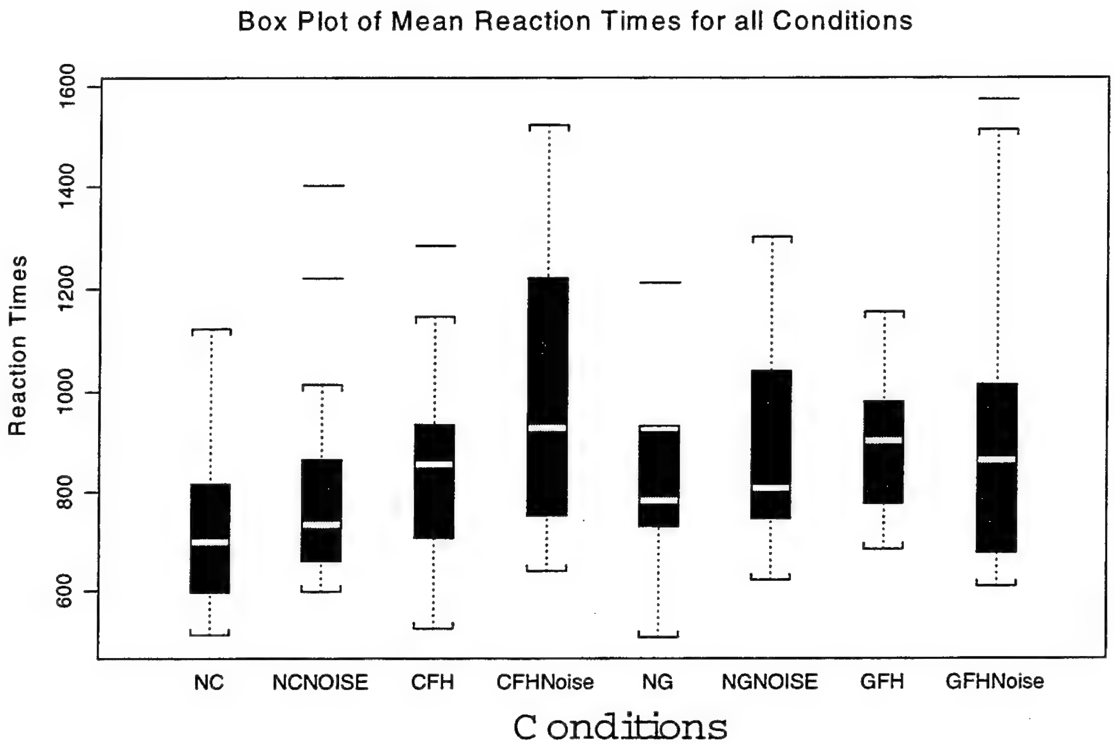
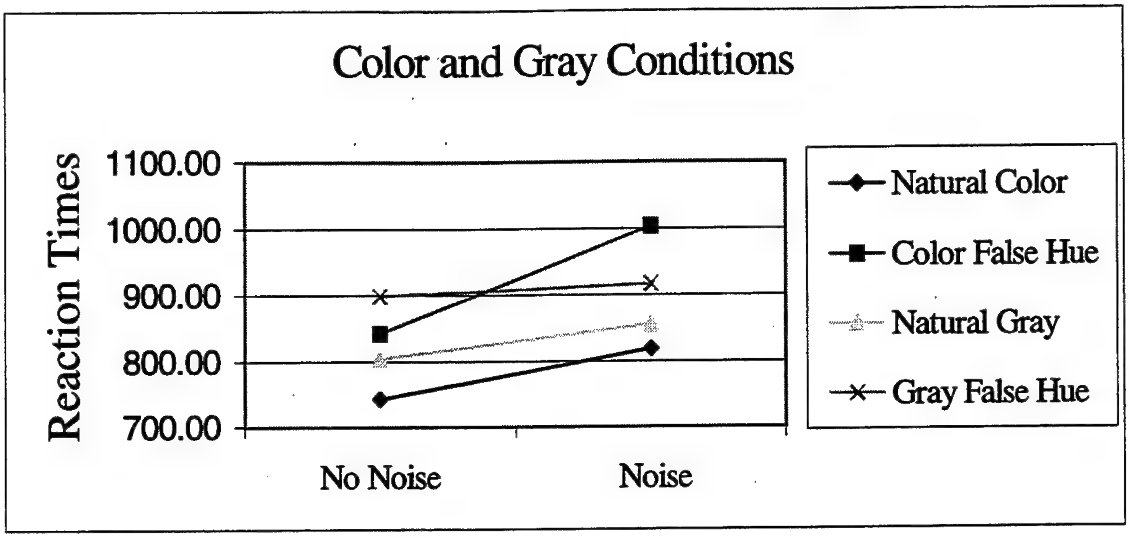


Figure 22: Box Plot of all image conditions mean reaction times



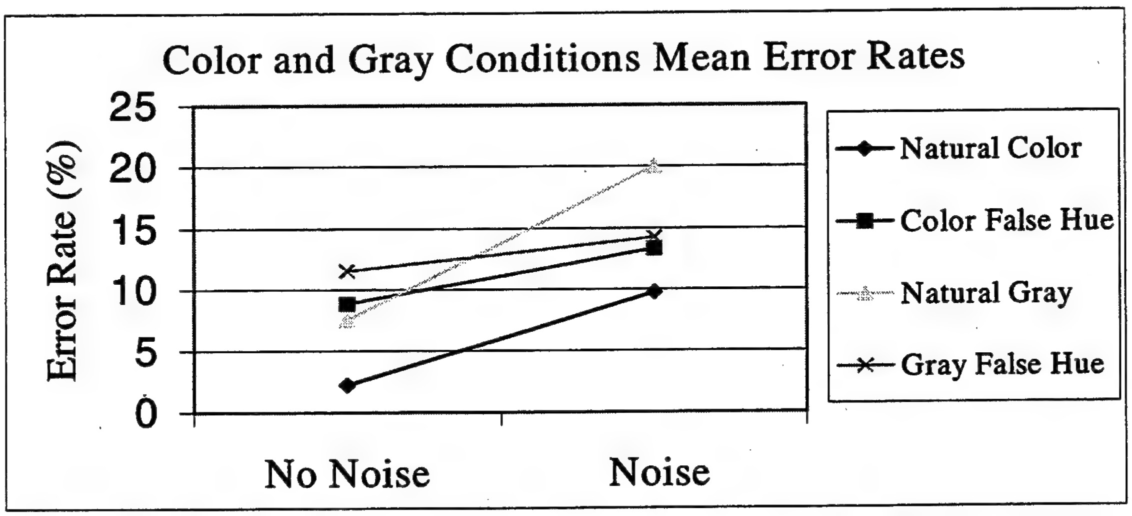


Figure 23: Line Plots of mean reaction times and error rates for Color and Gray conditions with "No Noise" and "Noise."

	NATURAL				GRAY			
DIFF	**NC**	**NCNOISE**	**CFH**	**CFHNOISE**	**NG**	**NGNOISE**	**GFH**	**GFHNOISE**
MEAN RT	742.65	817.78	841.66	1003.24	803.94	855.38	899.29	917.00
SEM	44.72	59.15	50.67	74.33	42.34	47.56	36.38	76.77
MEAN Err	2.22	9.78	8.89	13.33	7.56	20.00	11.55	14.22
SEM	1.06	2.59	1.25	2.84	1.70	2.25	2.00	2.14

Table 9: Tabulated data for image condition reaction time and error rate means

Where NCNOISE represents natural color with noise;

CFHNOISE represents color false hue with noise;

NGNOISE represents natural gray with noise and

GFHNOISE represents gray false hue with noise.

By inspection of the box plot, a large difference in each condition's reaction time medians across all conditions is seen. This suggests that participant response rates are affected by a particular image presentation. The large variance of the data also suggests that participant performance is affected. The interquartile range comparison between conditions of noise and those conditions without noise shows that higher uncertainty in response times exists for noisy conditions. It is interesting to note that the false color and false gray noise conditions that were manipulated for hue are excessively large which suggests a severe disruption of participant performance when viewing these particular image conditions. There are fewer outliers displayed than what was seen in the previous experiment, presumably because the data is more dispersed overall. A single participant was responsible for every outlier except for one. The mean error rates observed in Table 9 shows a relationship that corresponds to the mean reaction times. The speed/accuracy relationship between conditions with noise and conditions without noise shows that participant's reaction time and error rates increased with the addition of noise. This implies that there was no speed/accuracy trade-off. For example, given that there is approximately a 52-millisecond difference in reaction time between conditions of natural gray with and without noise, the error rate for the noisier condition is approximately three times that of the no noise condition. Therefore, it is concluded that under conditions where error rates are similar, the difference in reaction times between conditions of natural gray with no noise and natural gray conditions with noise would be much greater. The line plots seem to confirm this observation. This effect applies to the hue and color conditions with noise when compared to the same conditions without noise, although not

at the same magnitude.

Before statistical analysis was conducted to determining whether noise has an effect on reaction times across all image conditions, the data obtained from images without noise was used to validate portions of the model used in the previous experiment. The previous experiment showed that altering an image's saturation has no effect on participant reaction time but altering the hue of an image does effect performance. Comparing the difference in reaction time and error rate means for hue will determine if using additional images validates the findings in Experiment 1. Under the hypothesis, there is a difference in the reaction times of these conditions. Table 10 shows this comparison.

		HUE		
DIFF	CFH-NC	GFH-NG	CFHNOISE-NCNOISE	GFHNOISE-NGNOISE
MEAN RT	99.01	95.36	185.47	17.70
SEM	25.24	29.68	43.65	56.62
MEAN Err	6.67	4.00	3.55	- 5.78
SEM	1.45	2.82	2.42	2.67

Table 10: Difference in reaction time and error rate means across all image conditions with and without Hue.

It is seen that there is a positive difference across all image conditions that are manipulated for hue, similar to the results for the previous experiment. This adds additional evidence that altering an image's hue causes participant reaction times to increase. There is a large difference between the color false hue noise and the natural color noise condition. This indicates that not only does changing hue have an effect on reaction time, but noise increases that effect. To test the data, a paired t-test using Bonferroni's inequalities with an $\alpha = 0.05$, four samples and a confidence level of 98.75% was used. When comparing the color false hue versus the natural color condition

reaction time ($\underline{t}(14) = 3.9232$ $\underline{p} \leq .0125$) and accuracy ($\underline{t}(14) = 4.5833$ $\underline{p} \leq .0125$), color false hue with noise versus natural color with noise condition reaction time ($\underline{t}(14) = 4.2491$ $\underline{p} \leq .0125$) and accuracy ($\underline{t}(14) = 1.4176$ $\underline{p} \geq .0125$), gray false hue versus natural gray condition reaction time ($\underline{t}(14) = 3.2129$ $\underline{p} \leq .0125$) and accuracy ($\underline{t}(14) = 1.467$ $\underline{p} \geq .0125$), an effect is found. These results validate the findings from Experiment 1. The exception is that in Experiment 1, no effect was found between gray false hue and natural gray. For an unknown reason, there is a larger reaction time and error rate difference in this experiment than compared to the previous experiment. No explanation can be made concerning this result. The gray false hue with noise versus natural gray with noise condition reaction time ($\underline{t}(14) = 1.3281$ $\underline{p} \geq .0125$) and accuracy ($\underline{t}(14) = -2.1619$ $\underline{p} \geq .0125$) shows no effect.

To validate the effect of color, we compare the differences between the means of each color condition with the same images in the achromatic condition as seen in Experiment 1. For a condition of color to be a factor, there will be a difference in the means across each condition. Table 11 displays the results.

		GRAY-COLOR		
DIFF	**NG-NC**	**NGNOISE-NCNOISE**	**GFH-CFH**	**GFHNOISE-CFHNOISE**
MEAN RT	61.29	37.60	57.63	-86.25
SEM	16.05	38.30	32.67	55.00
MEAN Err	5.33	10.22	2.67	0.89
SEM	1.62	3.11	1.93	2.24

Table 11: Difference in reaction time and error rate means across all image conditions between Color and Monochrome

It is shown that there exists a difference across all conditions. A significant finding in this experiment that differs from the previous experiment findings is that the reaction time difference between the gray false hue and color false hue is positive

indicating that participants viewed the achromatic format slower. The only explanation for this contradiction may be that participants reacted with more caution in selecting the proper orientation. An error rate comparison between the gray false hue and color false hue shows that the error rate is less in this experiment. This delay in image selection contributes to the increase in reaction time and reduced error rate. The remaining conditions contain a positive value indicating that images viewed with color will enable a participant to respond faster. In tests of the data, a paired t-test using Bonferroni's inequalities with an $\alpha = 0.05$, four samples and a confidence level of 98.75% was used. When comparing the natural gray versus the natural color condition reaction time ($t(14) = 3.8183$ $p \leq .0125$) and accuracy ($t(14) = 3.2922$ $p \leq .0125$), and natural gray with noise versus natural color with noise condition reaction time ($t(14) = 0.9818$ $p \geq .0125$) and accuracy ($t(14) = 3.2859$ $p \leq .0125$) an effect is shown. The natural gray with noise versus natural color with noise condition effect is contrary to the findings in the previous experiment. An explanation for this result may be due to the object size restriction when selecting experimental stimuli. Without the benefit of large objects, color played a key role in segmenting global features contained in the degraded images. The remaining conditions gray false hue versus color false hue condition reaction time ($t(14) = 1.7642$ $p \geq .0125$) and accuracy ($t(14) = 1.3813$ $p \geq .0125$), and gray false hue with noise versus color false hue with noise condition reaction time ($t(14) = -1.5682$ $p \geq .0125$) and accuracy ($t(14) = 0.3974$ $p \geq .0125$) showed no effect.

Finally, to compare an image that is spatially degraded by noise to an image that does not suffer from spatial degradation, we will determine if an effect of Gaussian noise exists. It is hypothesized that there is a difference in participant reaction time and error

rates between these types of images. By taking the difference of the means, there will be a difference in reaction times between each condition for noise. Table 12 displays the results.

	NOISE			
DIFF	**NCNOISE-NC**	**CFHNOISE-CFH**	**NGNOISE-NG**	**GFHNOISE-GFH**
MEAN RT	75.13	161.58	51.44	17.70
SEM	23.41	42.27	37.19	56.62
MEAN Err	7.56	4.44	12.44	2.67
SEM	2.24	2.81	2.33	2.97

Table 12: Difference in reaction time and error rate means across all image conditions with Noise and images without Noise

There exists an effect for noise under all image formats. In fact, there is a huge variability in the effect of noise on reaction times and error rate means with ranges from 17.70 to 161.58 milliseconds and 2.67 to 12.44 percent respectively. The standard errors for the reaction time means are very high and inconsistent across each condition. This shows that participants view images without noise much faster and more accurately than images that contain noise. All conditions contain a positive value that indicates that images that do not contain noise will decrease participant reaction time. To test the data, a paired t-test using Bonferroni's inequalities with an $\alpha = 0.05$, four samples and a confidence level of 98.75% was used to test the data. When comparing the natural color with noise versus the natural color condition reaction time ($\underline{t}(14) = 3.2093$ $\underline{p} \leq .0125$) and accuracy ($\underline{t}(14) = 3.3712$ $\underline{p} \leq .0125$), color false hue with noise versus the color false hue condition reaction time ($\underline{t}(14) = 3.8228$ $\underline{p} \leq .0125$) and accuracy ($\underline{t}(14) = 1.5811$ $\underline{p} \geq .0125$), and natural gray noise versus the natural gray condition reaction time ($\underline{t}(14) = 1.3831$ $\underline{p} \geq .0125$) and accuracy ($\underline{t}(14) = 5.3324$ $\underline{p} \leq .0125$), an effect exists. However, when comparing the gray false hue noise versus the gray false hue condition reaction

time ($t(14) = 0.3127$ $p \geq .0125$) and accuracy ($t(14) = 0.8993$ $p \geq .0125$) no effect is shown. This implies that color images that lack visual clarity are effected by this deficiency more than achromatic images.

To further validate the visual model for this experiment, the second method of statistical analysis is employed in the previous experiment was repeated. A combined one-sided t-test was conducted for individual image conditions using an $\alpha = 0.5$. By grouping individual conditions of a particular group (Figure 24) and comparing these conditions reaction time and error rate means to those conditions that do not possess the groups stated manipulations, the following results are shown in Table 13.

<u>COMPARING HUES</u>

Color False Hue	⟷	Natural Color
Color False Hue and Noise	⟷	Natural Color and Noise
Gray False Hue	⟷	Natural Gray
Gray False Hue and Noise	⟷	Natural Gray and Noise

Figure 24: Stacked comparison of all viewing conditions with and without Hue manipulated

Difference between Hue and non-Hue conditions	
Mean	110.36
SEM	19.14
Mean Err	2.11
SEM	1.32

Table 13: Reaction time and error rate means for images manipulated for Hue

Based on the data provided in Table 13, there is evidence that a reaction time ($t(59) = 5.767$ $p \leq .05$) and accuracy ($t(59) = 1.5977$ $p \geq .05$) effect exists. This effect is

also present in Experiment 1 and is validated in this experiment. These results provide evidence that manipulating an image's hue will disrupt participant visual perception.

To determine if a color effect exists, reaction time and error rate means for color are compared to the achromatic images. This comparison will determine whether color is more beneficial in object recognition than in achromatic images. Figure 25 shows these conditions.

COMPARING COLOR

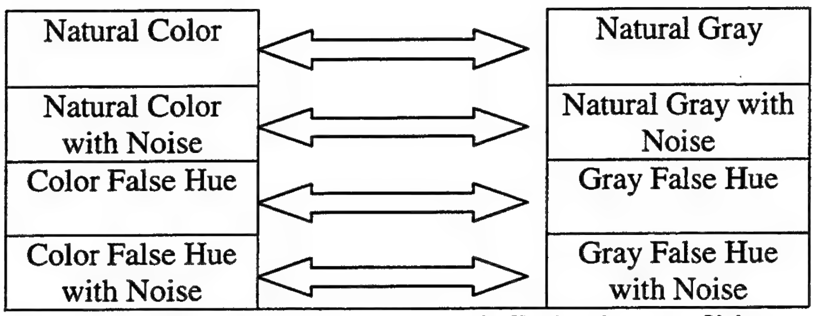


Figure 25: Stacked comparison of all viewing conditions with and without Color

Difference between Color and achromatic conditions	
Mean	-17.57
SEM	20.18
Mean Err	4.78
SEM	1.21

Table 14: Reaction time and error rate means for images with and without Color

As observed in Table 14, there exists significant evidence of an accuracy effect for the reaction time ($\underline{t}(59) = -0.8706$ $\underline{p} \geq .05$) and accuracy ($\underline{t}(59) = 3.9562$ $\underline{p} \leq .05$). In fact, as seen in the previous experiment, participants respond to achromatic images slightly faster than colored images. This result can be misleading given that it has been shown that altering an images hue affects participant reaction time. As described in the

previous experiment, by increasing the degrees of freedom by combining all color conditions and comparing reaction time and error rate means against all achromatic condition reaction time and error rate means, the effect of hue is reduced by the addition of the other conditions.

Lastly, to examine the effect of noise, reaction time and error rate means are compared. Figure 26 shows these conditions.

COMPARING NOISE

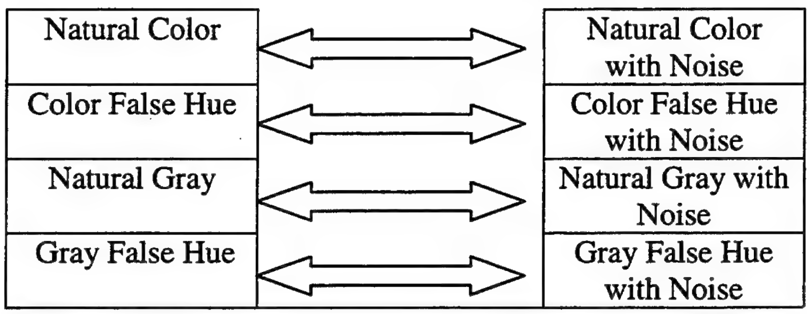


Figure 26: Stacked comparison of all viewing conditions with and without Noise

Difference between Images with Noise to Images without Noise	
Mean	76.46
SEM	21.42
Mean Err	6.78
SEM	1.36

Table 15: Reaction time and error rate means for images with and without Noise

As observed in Table 15, there exists evidence of a significant effect for reaction time ($t(59) = 3.5702$ $p \leq .05$) and accuracy ($t(59) = 4.9897$ $p \leq .05$). It is also seen that images with noise are responded to slower than clear images.

D. DISCUSSION

The purpose of this experiment is to clarify the role of color in object recognition

when viewing spatially degraded imagery. It is hypothesized that natural color would enhance object recognition for images that are degraded with noise.

The principle research that questioned the role of color in object recognition was conducted by Wurm, et al., (1993). This research used degraded food images to determine color's role. It was found that color aided the recognition of objects in blurred and unblurred conditions.

This experiment used natural scenes for stimuli taken from a professionally photographed commercial CD. The reason for using natural scenes was to closely approximate imagery that may be found on military night vision displays. These displays are small which hinders image resolution. The images were presented in either natural color or achromatic condition or manipulated by altering the hue. Gaussian noise was also added to half of the images.

Analysis of the data provided a means to validate the findings of Experiment 1. When comparing the combined conditions of natural hue with unnatural hue, an effect was found. This effect validates the findings in the previous experiment. These overwhelming results strongly suggest that the HVS is disrupted when an images natural color is altered. Individually, all image conditions of false hue were compared to the natural hue conditions. The findings of this experiment validate the findings obtained in Experiment 1.

When the combined conditions of color were compared to the achromatic conditions, an effect was found. This effect validates previous experiment findings. When comparing images that are achromatic with those that display color, either false or natural, color appears to play an important role in object recognition. Individually, all

image conditions of false hue were compared to natural hue conditions. The findings of this experiment validate the findings of Experiment 1. When a natural color scene is modified by altering the color, independent of image clarity, the HVS is negatively disrupted by the color change. However, the findings in this experiment also revealed an effect between gray false hue versus natural gray that contradicts the findings in Experiment 1. No adequate explanation can be determined to explain this effect.

All conditions were individually compared for color and the results differed from the color results found in Experiment 1. An effect was found between natural color and natural gray conditions, independent of image clarity. The most likely explanation for the significance of color in object recognition found in this experiment is that objects contained in the natural scenes are smaller and less pronounced as compared to objects in Experiment 1 stimuli. A criterion for this experiment was that objects could not encompass more than approximately 25 percent of the visual field of view. This reduction in object size required the participant to globally process the entire scene instead of identifying a particular object. Therefore, spatial segmentation of individual objects was nullified and global scene processing occurred. It was shown that natural color was beneficial in scenes that required global processing. However, when the color is altered, no effect is evident when compared to the achromatic format. The reaction times for color false hue were much less than the reaction times for gray false hue in this experiment. This result is completely opposite to the comparison found in Experiment 1. Although not significant, it suggests that any type of color may benefit object recognition and the HVS is disrupted less for scenes that are processed globally using artificial color.

A significant effect exists between scenes that are spatially degraded and scenes

that contain adequate resolution. This result validates previous research on the importance of color with degraded imagery. Without the benefit of identifying objects by profile and surface features, color (natural and false) is significantly important in the segmentation of boundaries.

The results of this experiment validate previous findings in that altering an image by modifying the color disrupts the HVS. Images are more efficiently processed in achromatic format than in the unnatural state. For scenes that are processed globally, color enhances object recognition.

Whether observing imagery that is either degraded or clear, the role of natural color is significant in object recognition. When the color of the scene is modified from the natural state, the HVS is disrupted and therefore is less efficient in object recognition. It is recommended that scenes be represented achromatically if natural color cannot be attained.

V. CONCLUSIONS, AND RECOMMENDATIONS

The objective of this thesis was to evaluate natural and artificial color on natural scene perception. Following an extensive review of previous research concerning the role of color in object recognition, it was determined that color generally played a specific role in enhancing the recognition of objects, but this role was only secondary to identification by object profile. It was also shown that depending on the experimental methodologies used when conducting the research, the role of color was often inconclusive. Some of the deficiencies found in previous research experimental methodologies were the inadequacy of target availability. Also, "natural" targets were poorly categorized as living, man-made or non-living objects, and the targets were never presented in the natural environment in which they belonged. For instance, an apple was placed on a flat surface against a neutral background and was either applied color or remained as a line drawing. The apple was never located in a tree or placed on the ground near the tree to provide other visual cues. Tasks were conducted in a controlled fashion, normally a naming or verification task. Other experiments altered the edge definition of the objects or provided atypical color schemes to determine color's role. Yet, not one of these experiment methodologies applied object recognition in a global scene.

The foundation of this thesis was to determine whether the derived research conclusions of the role of color could be applied to objects in a global scene. By selecting images from an enormous sample of images using strict selection criteria, this thesis was able to test the various color theories. The hypothesis developed from the research was that when comparing naturally colored scenes to false colored scenes,

participant reaction times and error rates would be different. Using professionally photographed scenes taken from various categories, it was presumed that a naturally colored scene would be viewed similarly as the scene in achromatic format. However, when the scene was altered by changing its natural state, the HVS would be disrupted when tasked to properly identify the orientation of the scene.

A second hypothesis tested the role of color and artificial color in a global environment that was spatially degraded by noise. Using the abundance of scenes that were available to conduct the research, it was hypothesized that color would aid in object recognition when compared to achromatic representations of the scene but artificially colored scenes would hinder the recognition process.

The results of both experiments were conclusive. When comparing prototypical colored scenes to the achromatic version of the scene using defined edge definitions, it was found that natural color did not significantly enhance object recognition. Although participant reaction times were slightly smaller for color, statistical analysis found this effect to be non-significant. This finding confirms the majority of conclusions found in prior research, that color does not benefit object recognition. However, when the color was altered to an atypical or unnatural representation, participant reaction time increased significantly; therefore it was concluded the effects of color on object recognition were significant. This important result is perhaps the most significant reason that contradictions exist from previous research. Vision scientists often fail to distinguish between natural and artificial color. If given the choice of recognizing an object in an atypically colored scene, it was preferred to eliminate artificial color from the scene. Additionally, changing the level of brightness to the scene had no effect on participant

reaction time for color.

Natural color becomes more important when the visual acuity of the scene degrades. The second experiment validated previous claims on colors role in object recognition for degraded images. When compared to the same scene with the addition of noise, color improved the ability to respond to object recognition. Therefore, it was concluded that color enhances object recognition for degraded scenes when compared to a monochromatic representation.

Current military research in NVD technology has provided the technology to combine various scenes into a simple representation to reduce individual component limitations and provide potential strengths. However, technology has permitted researchers to apply color to image representations that originate outside the range of the HVS's sensitivity. The ability to provide standardized colors to the global scene is the subject of much skepticism that questions this feasibility. The conclusions drawn from this thesis provides evidence that color is beneficial when viewing spatially degraded imagery. However, with scenes that are not spatially degraded, natural color is more effective for object recognition when the scene is viewed globally.

Further research is required to validate the conclusions of this study. First, the images chosen for these experiments were commercially photographed scenes. It is recommended that identical procedures be employed with images taken from fused sensors. The addition of noise in the second experiment was to approximate the lack of visual resolution found in small military displays. By utilizing real-world images taken from sensors employed in the field, these approximations would be unnecessary.

Second, a different task should be utilized to properly identify an object within the

scene. Although this type of experiment could potentially limit the number of participants that may be available, objects can be chosen that pertain to a participant's particular specialty. Therefore, the participant's level of expertise could be tightly controlled.

Third, conduct the viewing on a display that approximates smaller military displays instead of a computer color monitor that contains resolution features not found on field equipment. This would add additional realism to field-testing. Finally, by varying the degree of image saturation and hue manipulation, a determination can be of the amount an image can be altered before participant perceptual degradation occurs.

The concept of providing color to fused displays will one day enable viewing a night time environment be seen as a natural daylight scene. However, much research is needed to validate the utilities of these technical achievements.

APPENDIX A: COMPUTER CODE FOR EXPERIMENT ONE (WRITTEN IN 'C')

```
#define _cdecl
#include <stdio.h>
#include <stdlib.h>
#include <conio.h>
#include <stddef.h>
#include <string.h>
#include <time.h>
#include <vrg.h>
#include <patch.h>
#include <story.h>
#include <keys.h>
#include <file.h>

#define FIXATION 1
#define STIMULI 2

#define NUMBER_OF_IMAGES 240
#define NUMBER_OF_PRACTICE_IMAGES 30

//keys '1' and '2' will stop interval
//keylist must be NULL terminated
VstoryKey keylist[] = {{'1', VSTOP},{'2', VSTOP},{'q',VSTOP},
{13, VSTOP},{NULL}};

int Ran(int max);
void Permute(int* array, int length);
void main(void)
{
short j,x,y,z;
char response, answer[3], subject[10],logfile[20]={"fin_"};
long latency;
FILE *fp;
FILE *fp2;
FILE *fp3;
char Image[NUMBER_OF_IMAGES][10]={"f001.pcx","f002.pcx","f003.pcx",
"f004.pcx","f005.pcx","f006.pcx","f007.pcx","f008.pcx","f009.pcx",
"f010.pcx","f011.pcx","f012.pcx","f013.pcx","f014.pcx","f015.pcx",
"f016.pcx","f017.pcx","f018.pcx","f019.pcx","f020.pcx","f021.pcx",
"f022.pcx","f023.pcx","f024.pcx","f025.pcx","f026.pcx","f027.pcx",
"f028.pcx","f029.pcx","f030.pcx","f031.pcx","f032.pcx","f033.pcx",
"f034.pcx","f035.pcx","f036.pcx","f037.pcx","f038.pcx","f039.pcx",
"f040.pcx","f041.pcx","f042.pcx","f043.pcx","f044.pcx","f045.pcx",
"f046.pcx","f047.pcx","f048.pcx","f049.pcx","f050.pcx","f051.pcx",
"f052.pcx","f053.pcx","f054.pcx","f055.pcx","f056.pcx","f057.pcx",
"f058.pcx","f059.pcx","f060.pcx","f061.pcx","f062.pcx","f063.pcx",
"f064.pcx","f065.pcx","f066.pcx","f067.pcx","f068.pcx","f069.pcx",
"f070.pcx","f071.pcx","f072.pcx","f073.pcx","f074.pcx","f075.pcx",
"f076.pcx","f077.pcx","f078.pcx","f079.pcx","f080.pcx","f081.pcx",
"f082.pcx","f083.pcx","f084.pcx","f085.pcx","f086.pcx","f087.pcx",
"f088.pcx","f089.pcx","f090.pcx","f091.pcx","f092.pcx","f093.pcx",
"f094.pcx","f095.pcx","f096.pcx","f097.pcx","f098.pcx","f099.pcx",
"f100.pcx","f101.pcx","f102.pcx","f103.pcx","f104.pcx","f105.pcx",
"f106.pcx","f107.pcx","f108.pcx","f109.pcx","f110.pcx","f111.pcx",
"f112.pcx","f113.pcx","f114.pcx","f115.pcx","f116.pcx","f117.pcx",
"f118.pcx","f119.pcx","f120.pcx","f121.pcx","f122.pcx","f123.pcx",
"f124.pcx","f125.pcx","f126.pcx","f127.pcx","f128.pcx","f129.pcx",
"f130.pcx","f131.pcx","f132.pcx","f133.pcx","f134.pcx","f135.pcx",
```

```
"f136.pcx","f137.pcx","f138.pcx","f139.pcx","f140.pcx","f141.pcx",
"f142.pcx","f143.pcx","f144.pcx","f145.pcx","f146.pcx","f147.pcx",
"f148.pcx","f149.pcx","f150.pcx","f151.pcx","f152.pcx","f153.pcx",
"f154.pcx","f155.pcx","f156.pcx","f157.pcx","f158.pcx","f159.pcx",
"f160.pcx","f161.pcx","f162.pcx","f163.pcx","f164.pcx","f165.pcx",
"f166.pcx","f167.pcx","f168.pcx","f169.pcx","f170.pcx","f171.pcx",
"f172.pcx","f173.pcx","f174.pcx","f175.pcx","f176.pcx","f177.pcx",
"f178.pcx","f179.pcx","f180.pcx","f181.pcx","f182.pcx","f183.pcx",
"f184.pcx","f185.pcx","f186.pcx","f187.pcx","f188.pcx","f189.pcx",
"f190.pcx","f191.pcx","f192.pcx","f193.pcx","f194.pcx","f195.pcx",
"f196.pcx","f197.pcx","f198.pcx","f199.pcx","f200.pcx","f201.pcx",
"f202.pcx","f203.pcx","f204.pcx","f205.pcx","f206.pcx","f207.pcx",
"f208.pcx","f209.pcx","f210.pcx","f211.pcx","f212.pcx","f213.pcx",
"f214.pcx","f215.pcx","f216.pcx","f217.pcx","f218.pcx","f219.pcx",
"f220.pcx","f221.pcx","f222.pcx","f223.pcx","f224.pcx","f225.pcx",
"f226.pcx","f227.pcx","f228.pcx","f229.pcx","f230.pcx","f231.pcx",
"f232.pcx","f233.pcx","f234.pcx","f235.pcx","f236.pcx","f237.pcx",
"f238.pcx","f239.pcx","f240.pcx"};

char Practice[NUMBER_OF_PRACTICE_IMAGES][10]={"p4.pcx","p5.pcx",
"p6.pcx","p7.pcx","p8.pcx","p9.pcx","p10.pcx","p11.pcx","p12.pcx",
"p13.pcx","p14.pcx","p15.pcx","p16.pcx","p17.pcx","p18.pcx",
"p19.pcx","p20.pcx","p21.pcx","p22.pcx","p23.pcx","p24.pcx",
"p25.pcx","p26.pcx","p27.pcx","p28.pcx","p29.pcx","p30.pcx",
"p31.pcx","p32.pcx","p33.pcx"};

char Path[16][50]={"d:\\final\\nc\\","d:\\final\\ng\\",
"d:\\final\\fh\\","d:\\final\\fs\\",
"d:\\final\\fhs\\","d:\\final\\fhg\\",
"d:\\final\\fsg\\","d:\\final\\fhsg\\",
"d:\\final\\unc\\","d:\\final\\ung\\",
"d:\\final\\ufh\\","d:\\final\\ufs\\",
"d:\\final\\ufhs\\","d:\\final\\ufhg\\",
"d:\\final\\ufsg\\","d:\\final\\ufhsg\\"};

char ThisImage[100];

int c[16] = {0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0};

int Order[NUMBER_OF_IMAGES], ThisTrial;

Vpatch_display_sequence_description list[2];

Vinit(VFULL);
Vpatch_init(NULL);
Vpatch_realize_message(VDISABLE);

for (y=0; y<NUMBER_OF_IMAGES; y++)
Order[y] = y;

Permute(Order, NUMBER_OF_IMAGES);

printf("\ntrying to open file\n");
if ((fp = Vfile_open("shw_imgs.stm", VTEXT, VREAD)) != NULL)
 {
  Vpatch_read(fp);
  Vfile_close(fp);
```

```
}
else
{
printf("\nCouldn't open the .stm file, dude.");
getch();
}

printf("\n\nWhat are this subjects initials?\n\t");
gets(subject);

strcat(logfile, subject);
strcat(logfile, ".dat");

fp2=fopen(logfile, "w");

list[0].interval_id = FIXATION;
list[0].keylist = NULL;

list[1].interval_id = STIMULI;
list[1].keylist = keylist;

Vpatch_realize(FIXATION);

//practice
for(y=0; y<NUMBER_OF_PRACTICE_IMAGES; y++){
printf("\nPress any key when ready to initiate trial");getch();
j=Ran(16);
strcpy(ThisImage, Path[j-1]);
strcat(ThisImage, Practice[y]);
Vimage_set_file(STIMULI, ThisImage);
printf("\n%s", ThisImage);
Vinterval_set_background_pct(STIMULI, 50.2,50.2, 50.2);
Vpatch_realize(STIMULI);
Vbeep();
Vpatch_display_sequence_wait(list, 2);
latency = list[1].nframes;
response = list[1].key;
if(j<9)
if((response-48)==2)
Verror_beep();
if (j>8)
if((response-48)==1)
Verror_beep();
Vpatch_unrealize(STIMULI);
if (response=='q'){
printf("\ntrying to quit");
break;
}
printf("\npractice trial number %d", y+1);
}

y=0;
x=0;
z=0;
for(y=0; y<NUMBER_OF_IMAGES;y++){
printf("\nPress any key when ready to initiate trial");getch();
ThisTrial = Order[y];
```

```
do{ j=Ran(16);} while (c[j-1] >= 15);
strcpy(ThisImage, Path[j-1]);
strcat(ThisImage, Image[ThisTrial]);
Vimage_set_file(STIMULI, ThisImage);
c[j-1]++;
printf("\n%s", ThisImage);
fprintf(fp2, "\n%d", y+1);
fprintf(fp2, "\t%s", ThisImage);
Vinterval_set_background_pct(STIMULI, 50.2,50.2, 50.2);
Vpatch_realize(STIMULI);
Vbeep();
Vpatch_display_sequence_wait(list, 2);
latency = list[1].nframes;
response = list[1].key;
if(j<9)
if((response-48)==2)
Verror_beep();
if (j>8)
if((response-48)==1)
Verror_beep();
Vpatch_unrealize(STIMULI);
if (response=='q'){
printf("\ntrying to quit");
break;
printf("\ntrial number %d", y+1);
fprintf(fp2, "\t%li", latency);
if(j<9)
fprintf(fp2, "\t1");
if(j>8)
fprintf(fp2, "\t2");
fprintf(fp2, "\t%c", response);
}
printf("\nThe experiment is over");
Vpatch_unrealize(FIXATION);
Vpatch_unrealize(STIMULI);
Vpatch_destroy();
fclose(fp2);
Vexit();
}
int Ran(int max)
//generate a random number between 1 & max
{
double x = RAND_MAX + 1.0;
int y;

y = 1 + rand() * (max/x);
return (y);
}

void Permute(int* array, int length)
//will permute a an array of length cells
{
int a, z, temp;
for (a=0; a<length; a++)
{       z = Ran(length - a) + a;
z--;    //subtract one so y can index an array
temp = array[z];
```

```
array[z] = array[a];
array[a] = temp;
}
}
```

APPENDIX B: COMPUTER CODE FOR EXPERIMENT TWO (WRITTEN IN 'C')

```
#define _cdecl
#include <stdio.h>
#include <stdlib.h>
#include <conio.h>
#include <stddef.h>
#include <string.h>
#include <time.h>
#include <vrg.h>
#include <patch.h>
#include <story.h>
#include <keys.h>
#include <file.h>
#define FIXATION 1
#define STIMULI 2
#define NUMBER_OF_IMAGES 240
#define NUMBER_OF_PRACTICE_IMAGES 30

//keys '1' and '2' will stop interval
//keylist must be NULL terminated
VstoryKey keylist[] = {{'1', VSTOP},
{'2', VSTOP},
{'q',VSTOP},
{13, VSTOP},
{NULL}};

int Ran(int max);
void Permute(int* array, int length);
void main(void)
{
short j,x,y,z, counter=0;
char response, answer[3], subject[10],logfile[20]={"jv4_"};
long latency;
FILE *fp;
FILE *fp2;
FILE *fp3;
char Image[NUMBER_OF_IMAGES][10]={"f01.pcx","f02.pcx","f03.pcx",
"f04.pcx","f05.pcx","f06.pcx","f07.pcx","f08.pcx","f09.pcx",
"f10.pcx","f11.pcx","f12.pcx","f13.pcx","f14.pcx","f15.pcx",
"f16.pcx","f17.pcx","f18.pcx","f19.pcx","f20.pcx","f21.pcx",
"f22.pcx","f23.pcx","f24.pcx","f25.pcx","f26.pcx","f27.pcx",
"f28.pcx","f29.pcx","f30.pcx","f31.pcx","f32.pcx","f33.pcx",
"f34.pcx","f35.pcx","f36.pcx","f37.pcx","f38.pcx","f39.pcx",
"f40.pcx","f41.pcx","f42.pcx","f43.pcx","f44.pcx","f45.pcx",
"f46.pcx","f47.pcx","f48.pcx","f49.pcx","f50.pcx","f51.pcx",
"f52.pcx","f53.pcx","f54.pcx","f55.pcx","f56.pcx","f57.pcx",
"f58.pcx","f59.pcx","f60.pcx","f61.pcx","f62.pcx","f63.pcx",
"f64.pcx","f65.pcx","f66.pcx","f67.pcx","f68.pcx","f69.pcx",
"f70.pcx","f71.pcx","f72.pcx","f73.pcx","f74.pcx","f75.pcx",
"f76.pcx","f77.pcx","f78.pcx","f79.pcx","f80.pcx","f81.pcx",
"f82.pcx","f83.pcx","f84.pcx","f85.pcx","f86.pcx","f87.pcx",
"f88.pcx","f89.pcx","f90.pcx","f91.pcx","f92.pcx","f93.pcx",
"f94.pcx","f95.pcx","f96.pcx","f97.pcx","f98.pcx","f99.pcx",
"f100.pcx","f101.pcx","f102.pcx","f103.pcx","f104.pcx",
"f105.pcx","f106.pcx","f107.pcx","f108.pcx","f109.pcx",
"f110.pcx","f111.pcx","f112.pcx","f113.pcx","f114.pcx",
"f115.pcx","f116.pcx","f117.pcx","f118.pcx","f119.pcx",
"f120.pcx","f121.pcx","f122.pcx","f123.pcx","f124.pcx",
```

```
"f125.pcx","f126.pcx","f127.pcx","f128.pcx","f129.pcx",
"f130.pcx","f131.pcx","f132.pcx","f133.pcx","f134.pcx",
"f135.pcx","f136.pcx","f137.pcx","f138.pcx","f139.pcx",
"f140.pcx","f141.pcx","f142.pcx","f143.pcx","f144.pcx",
"f145.pcx","f146.pcx","f147.pcx","f148.pcx","f149.pcx",
"f150.pcx","f151.pcx","f152.pcx","f153.pcx","f154.pcx",
"f155.pcx","f156.pcx","f157.pcx","f158.pcx","f159.pcx",
"f160.pcx","f161.pcx","f162.pcx","f163.pcx","f164.pcx",
"f165.pcx","f166.pcx","f167.pcx","f168.pcx","f169.pcx",
"f170.pcx","f171.pcx","f172.pcx","f173.pcx","f174.pcx",
"f175.pcx","f176.pcx","f177.pcx","f178.pcx","f179.pcx",
"f180.pcx","f181.pcx","f182.pcx","f183.pcx","f184.pcx",
"f185.pcx","f186.pcx","f187.pcx","f188.pcx","f189.pcx",
"f190.pcx","f191.pcx","f192.pcx","f193.pcx","f194.pcx",
"f195.pcx","f196.pcx","f197.pcx","f198.pcx","f199.pcx",
"f200.pcx","f201.pcx","f202.pcx","f203.pcx","f204.pcx",
"f205.pcx","f206.pcx","f207.pcx","f208.pcx","f209.pcx",
"f210.pcx","f211.pcx","f212.pcx","f213.pcx","f214.pcx",
"f215.pcx","f216.pcx","f217.pcx","f218.pcx","f219.pcx",
"f220.pcx","f221.pcx","f222.pcx","f223.pcx","f224.pcx",
"f225.pcx","f226.pcx","f227.pcx","f228.pcx","f229.pcx",
"f230.pcx","f231.pcx","f232.pcx","f233.pcx","f234.pcx",
"f235.pcx","f236.pcx","f237.pcx","f238.pcx","f239.pcx",
"f240.pcx"};

char Practice[NUMBER_OF_PRACTICE_IMAGES][10]={"p04.pcx",
"p05.pcx","p06.pcx","p07.pcx","p08.pcx","p09.pcx","p10.pcx",
"p11.pcx","p12.pcx","p13.pcx","p14.pcx","p15.pcx","p16.pcx",
"p17.pcx","p18.pcx","p19.pcx","p20.pcx","p21.pcx","p22.pcx",
"p23.pcx","p24.pcx","p25.pcx","p26.pcx","p27.pcx","p28.pcx",
"p29.pcx","p30.pcx","p01.pcx","p02.pcx","p03.pcx"};

char Path[16][50]= {"d:\\final2\\nc\\","d:\\final2\\ng\\",
"d:\\final2\\fc\\","d:\\final2\\fg\\",
"d:\\final2\\noise_c\\","d:\\final2\\noise_g\\",
"d:\\final2\\noise_fc\\","d:\\final2\\noise_fg\\",
"d:\\final2\\unc\\","d:\\final2\\ung\\",
"d:\\final2\\ufc\\","d:\\final2\\ufg\\",
"d:\\final2\\unoise_c\\","d:\\final2\\unoise_g\\",
"d:\\final2\\unose_fc\\","d:\\final2\\unose_fg\\"};

char ThisImage[100];
int c[16] = {0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0};
int Order[NUMBER_OF_IMAGES], ThisTrial;
Vpatch_display_sequence_description list[2];
Vinit(VFULL);
Vpatch_init(NULL);
Vpatch_realize_message(VDISABLE);

for (y=0; y<NUMBER_OF_IMAGES; y++)
Order[y] = y;
Permute(Order, NUMBER_OF_IMAGES);
printf("\ntrying to open file\n");
if ((fp = Vfile_open("shw_imgs.stm", VTEXT, VREAD)) != NULL)
{
Vpatch_read(fp);
Vfile_close(fp);
```

```
}
else
{
printf("\nCouldn't open the .stm file, dude.");getch();
}
printf("\n\nWhat are this subjects initials?\n\t"); gets(subject);
strcat(logfile, subject);
strcat(logfile, ".dat");
fp2=fopen(logfile, "w");
list[0].interval_id = FIXATION;
list[1].interval_id = STIMULI;
list[1].keylist = keylist;
Vpatch_realize(FIXATION);
printf("\nPress any key to begin practice phase");getch();
//practice
for(y=0; y<NUMBER_OF_PRACTICE_IMAGES; y++){
j=Ran(16);
strcpy(ThisImage, Path[j-1]);
strcat(ThisImage, Practice[y]);
Vimage_set_file(STIMULI, ThisImage);
printf("\n%s", ThisImage);
Vinterval_set_background_pct(STIMULI, 50.2,50.2, 50.2);
Vpatch_realize(STIMULI);
Vbeep();
Vpatch_display_sequence_wait(list, 2);
latency = list[1].nframes;
response = list[1].key;
if(j<9)
if((response-48)==2)
Verror_beep();
if (j>8)
if((response-48)==1)
Verror_beep();
Vpatch_unrealize(STIMULI);
if (response=='q'){
printf("\ntrying to quit");
break;
}
printf("\npractice trial number %d", y+1);
}

printf("\nPractice phase over, press any key to begin experiment");
getch();
y=0;
x=0;
z=0;
for(y=0; y<NUMBER_OF_IMAGES;y++){
counter++;
if(counter%30==0){
printf("\nTake a break, press any key when ready to continue");
getch();
}
ThisTrial = Order[y];
do{ j=Ran(16);} while (c[j-1] >= 15);
strcpy(ThisImage, Path[j-1]);
strcat(ThisImage, Image[ThisTrial]);
Vimage_set_file(STIMULI, ThisImage);
```

```
c[j-1]++;
printf("\n%s", ThisImage);
fprintf(fp2, "\n%d", y+1);
fprintf(fp2, "\t%s", ThisImage);
Vinterval_set_background_pct(STIMULI, 50.2,50.2, 50.2);
Vpatch_realize(STIMULI);
Vbeep();
Vpatch_display_sequence_wait(list, 2);
latency = list[1].nframes;
if(j<9)
if((response-48)==2)
Verror_beep();
if (j>8)
if((response-48)==1)
Verror_beep();
Vpatch_unrealize(STIMULI);
if (response=='q'){
printf("\ntrying to quit");
break;
}
printf("\ntrial number %d", y+1);
fprintf(fp2, "\t%li", latency);
if(j<9)
fprintf(fp2, "\t1");
if(j>8)
fprintf(fp2, "\t2");
fprintf(fp2, "\t%c", response);
}
printf("\nThe experiment is over");
Vpatch_unrealize(FIXATION);
Vpatch_unrealize(STIMULI);
Vpatch_destroy();
fclose(fp2);
Vexit();
}
int Ran(int max)
//generate a random number between 1 & max
{
double x = RAND_MAX + 1.0;
int y;
y = 1 + rand() * (max/x);
return (y);
}
void Permute(int* array, int length)
//will permute a an array of length cells
{
int a, z, temp;

for (a=0; a<length; a++)
{z = Ran(length - a) + a;
z--;//subtract one so y can index an array
temp = array[z];
array[z] = array[a];
array[a] = temp;
}
}
```

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX C: EXPERIMENT ONE REACTION TIME AND ACCURACY DATA

	Color				Gray			
	NC	CFH	CFS	CFHS	NG	GFH	GFS	GFHS
SUBJ 1	486.47	601.43	483.74	533.12	473.62	503.69	569.22	513.49
SUBJ 2	622.97	782.38	582.54	712.81	595.87	740.81	602.32	663.62
SUBJ 3	577.15	848.55	594.21	660.63	673.06	636.65	710.83	790.07
SUBJ 4	450.42	543.12	479.57	483.14	480.17	515.90	488.14	505.16
SUBJ 5	1066.24	1691.55	888.34	1620.19	847.74	1332.24	1625.54	1396.24
SUBJ 6	513.68	554.78	559.39	629.75	511.70	533.12	488.14	559.39
SUBJ 7	562.00	615.31	558.71	677.71	600.32	700.32	615.03	683.66
SUBJ 8	497.42	536.69	543.12	538.89	632.44	542.56	489.09	598.57
SUBJ 9	613.09	804.68	708.61	693.31	742.56	719.58	758.59	623.24
SUBJ 10	845.22	1232.84	1394.44	1286.15	993.65	1272.27	1091.87	1783.22
SUBJ 11	463.51	504.56	459.94	486.12	453.15	407.53	461.35	468.56
SUBJ 12	586.99	604.25	631.80	567.63	576.99	499.11	565.25	605.06
SUBJ 13	533.68	641.41	710.43	955.17	798.01	701.00	693.95	653.63
SUBJ 14	504.56	631.41	538.25	588.87	519.79	503.64	485.92	555.33
SUBJ 15	799.68	873.46	1135.91	852.04	741.37	862.16	864.40	1180.30
SUBJ 16	712.54	624.75	613.45	648.55	614.75	603.93	713.41	673.45
SUBJ 17	552.00	813.96	570.61	598.09	657.48	580.54	634.19	635.46
SUBJ 18	469.46	488.00	543.24	577.04	537.61	501.31	515.07	574.77
SUBJ 19	547.56	678.30	714.60	635.86	590.24	638.85	580.32	549.19
SUBJ 20	616.42	729.20	584.38	778.86	1089.84	679.86	657.48	897.97
Mean RT	601.05	740.03	664.76	726.20	656.52	673.75	680.50	745.52
SEM	34.05	63.13	51.77	62.55	38.13	53.86	60.20	74.94

	Color				Gray			
	NC	CFH	CFS	CFHS	NG	GFH	GFS	GFHS
SUBJ 1	0.00	0.00	0.00	6.67	6.67	0.00	0.00	6.67
SUBJ 2	6.67	13.33	0.00	6.67	0.00	0.00	13.33	0.00
SUBJ 3	0.00	0.00	0.00	13.33	0.00	0.00	0.00	13.33
SUBJ 4	6.67	0.00	6.67	13.33	6.67	0.00	0.00	6.67
SUBJ 5	6.67	0.00	6.67	6.67	6.67	0.00	6.67	13.33
SUBJ 6	0.00	0.00	13.33	0.00	6.67	6.67	0.00	13.33
SUBJ 7	0.00	0.00	6.67	6.67	0.00	6.67	20.00	6.67
SUBJ 8	0.00	6.67	0.00	6.67	13.33	0.00	6.67	6.67
SUBJ 9	0.00	0.00	0.00	6.67	6.67	13.33	0.00	26.67
SUBJ 10	0.00	6.67	0.00	0.00	6.67	0.00	13.33	6.67
SUBJ 11	6.67	6.67	6.67	6.67	0.00	13.33	6.67	20.00
SUBJ 12	0.00	13.33	13.33	6.67	0.00	13.33	6.67	26.67
SUBJ 13	0.00	6.67	6.67	20.00	0.00	13.33	13.33	0.00
SUBJ 14	6.67	0.00	13.33	13.33	0.00	6.67	0.00	0.00
SUBJ 15	13.33	6.67	33.33	6.67	26.67	20.00	13.33	13.33
SUBJ 16	13.33	0.00	6.67	6.67	0.00	20.00	6.67	13.33
SUBJ 17	0.00	6.67	0.00	0.00	6.67	6.67	0.00	6.67
SUBJ 18	6.67	20.00	6.67	26.67	13.33	26.67	20.00	33.33
SUBJ 19	0.00	6.67	6.67	0.00	6.67	13.33	0.00	6.67
SUBJ 20	6.67	13.33	13.33	20.00	20.00	13.33	6.67	40.00
Mean RT	3.67	5.33	7.00	8.67	6.33	8.67	6.67	13.00
SEM	1.02	1.33	1.78	1.61	1.64	1.82	1.53	2.49

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX D: EXPERIMENT TWO REACTION TIME AND ACCURACY DATA

	NC	NC NOISE	CFH	CFH NOISE	NG	NG NOISE	GFH	GFH NOISE
SUBJ 1	687.19	733.30	888.3	1113.42	730.53	806.52	978.81	783.3
SUBJ 2	1122.73	1402.17	1283.84	1522.72	1211.62	1040.24	1154.95	1574.34
SUBJ 3	521.41	723.58	671.4	639.72	613.44	626.36	683.95	862.84
SUBJ 4	510.54	613.17	523.79	673.58	505.93	791.64	776.08	631.04
SUBJ 5	720.48	720.8	745.11	769.14	751.25	697.7	797.88	669.97
SUBJ 6	677.75	754.46	750.57	1250.78	799.97	833.3	979.82	742.28
SUBJ 7	802.19	808.3	934.58	1221.11	919.41	880.27	933.3	893.55
SUBJ 8	584.59	621.09	652.2	722.75	679.83	621.77	769.41	676.9
SUBJ 9	1028.53	1220.51	1145.79	1521.96	919.19	1300.78	1147.18	1513.83
SUBJ 10	698.31	660.09	993.55	848.68	781.52	821.12	801.25	874.32
SUBJ 11	815.44	864.85	728.82	883.99	849.37	745.8	987.78	940.24
SUBJ 12	596.64	598.19	706.38	751.89	745.48	754.83	751.08	608.9
SUBJ 13	807.19	799.41	855.32	927.94	888.65	1046.93	847.88	1186.62
SUBJ 14	687.19	733.3	888.3	1113.42	730.53	806.52	978.81	783.3
SUBJ 15	879.54	1013.43	856.98	1087.55	932.34	1056.87	901.23	1013.54
MEAN RT	742.65	817.78	841.66	1003.24	803.94	855.38	899.29	917.00
SEM	44.72	59.15	50.67	74.33	42.34	47.56	36.38	76.77

	NC	NC NOISE	CFH	CFH NOISE	NG	NG NOISE	GFH	GFH NOISE
SUBJ 1	0	0	13.33	0	0	6.67	13.33	6.67
SUBJ 2	0	0	0	0	0	20	0	6.67
SUBJ 3	6.67	20	6.67	13.33	13.33	20	13.33	26.67
SUBJ 4	0	20	6.67	20	6.67	13.33	0	26.67
SUBJ 5	13.33	33.33	13.33	33.33	13.33	26.67	13.33	26.67
SUBJ 6	0	13.33	6.67	33.33	13.33	26.67	20	13.33
SUBJ 7	0	20	13.33	13.33	0	26.67	20	13.33
SUBJ 8	0	13.33	0	0	20	13.33	0	13.33
SUBJ 9	6.67	0	6.67	20	13.33	33.33	20	20
SUBJ 10	0	6.67	13.33	13.33	6.67	13.33	13.33	13.33
SUBJ 11	6.67	6.67	13.33	20	6.67	33.33	13.33	20
SUBJ 12	0	6.67	13.33	13.33	13.33	20	0	6.67
SUBJ 13	0	0	6.67	6.67	6.67	26.67	20	0
SUBJ 14	0	0	13.33	0	0	6.67	13.33	6.67
SUBJ 15	0	6.67	6.67	13.33	0	13.33	13.33	13.33
MEAN Err	2.22	9.78	8.89	13.33	7.56	20.00	11.55	14.22
SEM	1.06	2.59	1.25	2.84	1.70	2.25	2.00	2.14

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

Adobe PhotoShop 4.0 Users Manual, Adobe Systems Inc., 1996.

Berry, F.C., Inventing the Future, How Science and Technology Transform the World, New York, NY: Macmillan, 1993.

Biederman, I. Teitelbaum, R.C., and Mezzanotte, R.J., (1983). Scene Perception: A Failure to Find a Benefit from Prior Expectancy or Familiarity. Journal Of Experimental Psychology, 9, 3.

Biederman, I., and Ju, G., (1988). Surface versus Edge-Based Determinants of Visual Recognition. Cognitive Psychology, 20.

Boyce, S.J., and Pollatsek, A., (1992). Identification of Objects in Scenes: The Role of Scene Background in Object Naming. Journal Of Experimental Psychology: Learning, Memory, and Cognition, 18, 3.

Boyce, S.J., Pollatsek, A., and Rayner, K., (1989). Effect of Background Information on Object Identification. Journal Of Experimental Psychology: Human Perception and Performance, 15, 3.

Brodie, E.E., Wallace, A.M., and Sharrat, B., (1991), Effect of Surface Characteristics and Style of Production on Naming and Verification of Pictorial Stimuli. American Journal of Psychology, 104, 4.

Campana, S.B., Passive Electro-Optical Systems, Volume 5, SPIE, 1993.

Christ, R.E., (1975), Review and Analysis of Color Coding Research for Visual Displays, Human Factors, 17.

Clausewitz, K.V., On War. Princeton University Press, 1976.

Eden, J., The Eye Book. New York, NY: Penguin Books, 1978.

Davidoff, J.B., and Ostergaard, A.L., (1985), Some Effects of Color on Naming and Recognition of Objects. Journal of Experimental Psychology: Learning, Memory and Cognition, 11.

Davidoff, J.B., and Ostergaard, A.L., (1988), The Role of Color in Categorical Judgments. Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 52.

De Valois, K.K., and Switkes, E. (1983), Simultaneous Masking Interactions between Chromatic and Luminance Gratings. Journal of the Optical Society of America, 73.

Essock, E.A., Sinai, M.J., McCarley, J.S., DeFord, J.K., and Srinivasan, N. (in review), Human Perceptual Performance with Nighttime Imagery: Region Recognition and Texture-based Segmentation.

FM 34-81-1 Battlefield Weather Effects, Department of the Army, Washington, D.C., 1992.

Gegenfurtner, K.J., (1997), Color in the Recognition of Natural Scenes. Invest. Ophthal. And Visual Sci (Suppl), 38 S900.

Hamilton, Lawrence C., Regression with Graphics: A Second Course in applied Statistics, Wadsworth Publishing Co: 1992.

Hartline, P.H., and Newman, E.A., The Infrared Vision of Snakes, Scientific American, 246, 3, 1982.

Jayle, Ourguad, Baisinger, Holmes and Duke-Elder, Night Vision, Springfield, VA: Thomas, 1959.

Joseph, J.E., and Proffitt, D.R., (1996), Semantic versus Perceptual Influences of Color in Object Recognition. Journal of Experimental Psychology: Learning, Memory, and Cognition, 22, 2.

Kissenger, Henry, Diplomacy, New York, NY: Simon and Shuster, 1994.

Klass, J., (1994), Uncooled, Cheap FLIRS to Open New Markets. Aviation Week and Space Technology).

Krebs, W.K., Scribner, D.A., Miller, G.M., Ogawa, J.S., and Schuler,J. (1998). Beyond Third Generation: A Sensor Fusion Targeting FLIR Pod for the F/A-18. Proceedings of the SPIE Conference on Synthetic Vision for Vehicle Guidance and Control, 2463.

Krebs, W.K., Scribner, D.A., Schuler, J., Miller. G.M., and Lobik, D. (1996). Human Factors Test and Evaluation of a Low Light Sensor Fusion Device for Automotive Applications. Society of Automotive Engineers, Detroit, MI.

LeGrand, Yves, Light Color and Vision. London, England: Chapman and Hill, 1968).

Markoff, J.I., (1972), Target Recognition Performance with Chromatic and Achromatic Displays (Research Rep. No. SRM-148). Minneapolis, MN: Honeywell.

Matlin, M.W., and Foley, H.J., Sensation and Perception, 4th ed. Allyn and Bacon: Mass., 1997.

MAWTS-1 (October, 1995). Helicopter night vision device manual. (Available from [Commanding Officer, MAWTS-1, Box 99200, Yuma, AZ 85369-9200]).

Night Vision and Electronic Sensors Directorate (NVESD), U.S. Army CECOM Research, Development and Engineering Center, Virginia: 1997.

Potter, E.B., Admiral Arleigh Burke, A Biography, New York, NY: Random House, 1990.

Polyak, S.l., The Vertebrate Visual System, Chicago: University of Chicago Press, 1957.

Price, C.J., and Humphreys, G.W., (1989), The Effects of Surface Detail in Object Categorization and Naming. Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 41(A).

Salvendy, G., Handbook of Human Factors and Ergonomics, 2nd edition, Wiley: 1997.

Sampson, M.T., An Assessmant of the Impact of Fused Monochrome and Fused Color Night Vision Displays on Reaction Time and Accuracy in Target Detection, Unpublished Master's Thesis Naval Postgraduate School, Monterey, CA., 1996.

Sampson, M.T., Krebs, W.K., Scribner, D.A., and Essock, E.A., (1996) Visual search in natural (visible, infrared and fused visible and infrared) stimuli. Investigative Ophthalmology and Visual Science, (SUPPL) 36, 1362, FT Lauderdale, FL.

Schlessinger, M., Infrared Technology Fundamentals, 2nd edition, New York, NY: 1995.

Schmidt, G.W., Hier, R.G., Benyamin, S., and DeForest, A.E. (1998). Real-time Locally Adaptive Contrast Enhancement of Medical Images by an Inexpensive Modular Image Processor. Medical Imaging II, Proceedings, SPIE-914.

Schwarzkopf, H. Norman, It Doesn't Take a Hero, New York, NY: Bantom Books, 1992.

Scribner, D.A., Satyshur, M.P., and Kruer, M.R., (1993). Composite Infrared Color Images and Related Processing. IRIS Specialty Group on Targets, Backgrounds and Discrimination, San Antonio, TX.

Scribner, D.A., Warren, P., Schuler, J., Satyshur, M., and Kruer, M., (1998). Infrared Color Fusion: An Approach to Sensor Fusion. Optics and Photonics News, 8.

Secular and Blake, Perception, 3rd edition: McGraw-Hill, Inc. 1994.

Sheppard, Joseph J., Human Color Perception, A Critical Study of the Experimental Foundation. New York, NY: American Elsevier Publishing Company, 1968.

Shumaker, D.L., Wood, J.T., and Thacker, C.R., Infrared Imaging Systems Analysis, DCS: 1988.

Steele, P.M., and Perconti, P., (1997). Part Task Investigation of MultiSpectural Image Fusion using Gray Scale and Synthetic Night Vision Sensor Imagery for Helicopter Pilotage. Proceedings of the SPIE Conference on Aerospace/Defense Sensing, Simulation, and Controls, 3062.

Steward, J.M., and Cole, B.L., (1989). What do Color Vision Defectives say about Everyday Tasks? Optometry and Vision Science, 66.

Time-Life Books, Commando Operations, The New Face of War, Virginia: Time Life Books, 1991.

Toet, A., IJspeert, J.K., Waxman, A.M., and Aguilar, M., (1997). Fusion of Visible and Thermal Imagery Improves Situational Awareness. Proceedings of the SPIE Conference on Enhanced and Synthetic Vision, 3088.

Toet, A., and Walraven, J., (1996). New False Color Mapping for Image Fusion. Optical Engineering, 35.

Triesman, A., (1985). Preattentive Processing in Vision. Computer Vision, Graphics, and Image Processing, 31.

Triesman, A., and Gelade, G., (1980). A Feature Integration Theory of Attention. Cognitive Psychology, 12.

Uttal, W.R., Baruch, T., and Allen, L. (1994). Phychophysical Foundations of a Model of Amplified Night Vision in Target Detection Tasks. Human Factors, 36.

Valdez, P., and Mehrabian, A. (1994). Effects of Color on Emotions. Journal of Experimental Psychology: General, 123,4.

Wandell, Brian A., Foundations of Vision, Sinauer Associates: Sunderland, Mass., 1995.

Waxman, A.M., Fay, D.A., Gove, A., Siebert, M., Racamato, J.P., Carrick, J.E., and Savoye, E.D. (1995). Color Night Vision: Fusion of Intensified Visible and Thermal IR Imagery. Proceedings of the SPIE Conference on Synthetic Vision for Vehicle Guidance and Control, 2463, 58-68.

Wolfe, J.M., (1994). The Pertinence of Research on Visual Search to Radiologic Practice. Academic Radiology, 2.

Wolfe, W.L., Introduction to Infrared System Design, SPIE, 1996.

Wurm, L.H., Legge., G.E., Isenberg, L.M., Luebker, A., (1993). Color Improves Object Recognition in Normal and Low Vision. Journal of Experimental Psychology: Human Perception and Performance, 19, 4.

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

No. Copies

1. Defense Technical Information Center 2
   8725 John J. Kingman Rd., STE 0944
   Fort Belvoir, VA 22060-6217

2. Dudley Knox Library 2
   Naval Postgraduate School
   411 Dyer Road
   Monterey, CA 93943-5101

3. Dr. W.K. Krebs, ...3
   Operations Research Department (Code OR/Kw)
   Naval Postgraduate School
   1411 Cunningham Rd.
   Monterey, CA 93942-5219

4. Dr. Samuel Buttrey 1
   Operations Research Department (Code OR/Bs)
   Naval Postgraduate School
   1411 Cunningham Rd.
   Monterey, CA 93942-5219

5. Dr. Jason McCarley 1
   Operations Research Department (Code OR/Mj)
   Naval Postgraduate School
   1411 Cunningham Rd.
   Monterey, CA 93942-5219

6. Dr. Mike Sinai...1
   Operations Research Department (Code OR/Ms)
   Naval Postgraduate School
   1411 Cunningham Rd.
   Monterey, CA 93942-5219

7. Naval Research Lab 1
   Attn: Dean Scribner, Code 5636
   Washington, DC 20378

8. LCDR John T. Vargo, USN 2
   587-B Sampson Ln
   Monterey, CA 93940

9. Joel Davis 1
Office of Naval Research
Code 342
800 North Quincy Street
Arlington, VA 22217-5660

10. Richard LeBlanc 1
LME&M
5600 Sandlake Rd
MP-126
Orlando, FL 32819-8907